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CHANGES IN HEALTH AND BEHAVIOR DURING THE BUSINESS CYCLE

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This dissertation considers to what extent changes in the unemployment rate – a proxy for the business cycle – drives changes in mortality and crime. I use a panel of U.S. counties from 1990 to 2013. I allow changes in the unemployment rate to have different effects upon mortality / crime in large versus small counties as well as between increases versus decreases in the unemployment rate. My results show great nuance along both these dimensions, suggesting that the effects of the business cycle are more subtle than what previous studies report. These results also give one greater insight into what factors could be driving these effects of the business cycle.

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INTRODUCTION

This dissertation explores nuances in health and crime using a sample of U.S. counties. Prior empirical research has explored changes in health as measured by the mortality rate during the business cycle, finding that mortality declines during recessions, but speculation arises as to why. Research in health economics is of crucial importance not only to the general public but also to policy makers as health care receives both great attention and extensive public funding.

Chapter 1 of this dissertation considers county-level mortality data from 1990 to 2013 and allows coefficients to differ between urban and rural counties. Allowing for these distinctions can help better uncover explanations for the pro-cyclical nature of mortality. Relatively higher opportunity costs of seeking medical treatment as well as higher stress levels during expansions are considered to be the primal reasons for pro-cyclicality of mortality. These factors could differ between urban and rural areas implying the association between unemployment and mortality rates to differ as well. I find that the negative association between unemployment and mortality more generally holds for urban areas. I also find death due to circulatory disease or influenza / pneumonia to be especially more prevalent in urban areas. This would suggest that higher pollution levels during economic booms could play a role. However, I also find this association to be strongest in counties ranging from 50,000 to 100,000 people. Presumably, these counties do not have the highest pollution levels. Moreover, I find little direct evidence that pollution drives our findings, suggesting that other characteristics of urban communities play more important roles.

Using linear models, most studies within this literature on aggregate health outcomes during cyclical fluctuations restrict the coefficient estimate upon unemployment to be the same across the business cycle. In Chapter 2, I employ a panel of U.S. counties from 1990 to 2013, and regress the mortality rate upon unemployment but allow the coefficient upon unemployment to vary depending upon whether there has been an increase or decrease in unemployment. That is, I allow the effect of booms upon mortality to be of a different magnitude than that of recessions. I also allow this asymmetry to vary depending upon the size of the county as perhaps asymmetries only arise for counties of a certain size. I find evidence of asymmetries – booms impact mortality more than do recessions. However, results do not coincide with those of chapter 1 in that mortality is found to be countercyclical in large counties but pro-cyclical in small ones.

Despite the abundant literature on how crime evolves over the business cycle, no consensus has arisen whether crime increases or decreases during recessions. The literature provides both positive and negative associations between the crime rate and the unemployment rate, a commonly used proxy for the business cycle. Chapter 3 revisits this issue and uses county-level crime data from 1990 to 2013. It allows for asymmetries in that associations between unemployment and crime can differ depending upon whether the unemployment rate is increasing or decreasing. I consider further nuance by allowing this asymmetry to vary depending upon the size of the county. Perhaps asymmetries only arise for metropolitan counties, for example. I again find evidence of asymmetries – decreases in the unemployment rate have stronger influences upon crime than do increases. Moreover, I also find substantial differences across county size. Unemployment and crime are positively associated in small counties but negatively associated in large ones.

CHAPTER 1

THE BUSINESS CYCLE AND MORTALITY: URBAN VERSUS RURAL COUNTIES

1.1 INTRODUCTION

The association between the business cycle and mortality has been extensively studied. Such studies include Ruhm (2000, 2013) for the United States, Neumayer (2004) for Germany, Tapia Granados (2005) for Spain, Gonzalez and Quast (2010) for Mexico, Ariizumi and Schirle (2012) for Canada, Lin (2009) for Pacific Asian countries, and Gerdtham and Ruhm (2006) for OECD countries. Using unemployment and mortality rates as proxies for business cycles and health outcomes, respectively, these studies report a pro-cyclical pattern of mortality at the state or national level. Mortality falls during recessions, a claim first promulgated over 90 years ago (Ogburn and Thomas, 1922) although Brenner (1973, 1975, and 1979) finds a countercyclical association.[1] How could mortality be pro-cyclical? For one, the opportunity cost of going to the doctor or of exercising and taking time to eat healthy is, presumably, higher during expansions than during recessions. Alternatively, people might push themselves harder during expansions such as work overtime or work multiple jobs. Such activities could cause more stress or allow them to become more susceptible to disease. Finally, during expansions people become wealthier and that might encourage them to take on risky activities such as excessive drinking or driving more recklessly thereby increasing fatality rates (Ruhm, 1995). In all of these cases, people's behavior changes across the business cycle and such changes hold ramifications for health in general and mortality, specifically.

When examining the U.S., the typical approach is to consider state-level variations in unemployment and mortality which is the approach first taken by Ruhm (2000). One might argue

[1] Moreover, many studies that use either family level data (Strully, 2009) or individual level data (Halliday, 2014; Sullivan and von Wachter, 2009; Gerdtham and Johannesson, 2005) find a countercyclical pattern of mortality rates with mortality rising during recessions.

that state-level data is not sufficiently refined as great differences could arise within states for both mortality and unemployment. Therefore, our study will use county-level data although use of such data is not free from errors either. First, using county-level data does not eliminate all of the possible variation that occurs within an observation but the smaller unit of analysis certainly diminishes the problem. Second, Pierce and Denison (2006) identify reporting errors from Texas using county-level data and such errors could be more prevalent with less aggregated data. We are not the first to apply county-level data to the issue of mortality and the business cycle. Fontenla, Gonzalez, and Quast (2011) focus on the race and ethnicity aspect of mortality and their results exhibit a pro-cyclical pattern of mortality for whites and Latinos but not for African-Americans.

A second reason to conduct a county-level analysis is that it can allow us to better understand what could be driving previous results by uncovering differences across distinct settings, in this case urban versus rural ones. For example, one reason that mortality could be pro-cyclical is that the opportunity cost of going to a doctor or seeking medical treatment is relatively high as people might find it costly to take time off from work. These opportunity costs could differ between urban and rural settings, especially if one might need to travel long distances to receive medical care or see a specialist in rural counties. If true, then the pro-cyclical association between mortality and unemployment should be stronger in rural areas. On the other hand, to the extent that stress contributes to mortality, that stress levels are higher in urban areas, and that stress is higher during expansions then the association between mortality and the business cycle should be stronger in urban areas. Moreover, to the extent that pollution rises during economic booms thereby contributing to mortality, then associations should be stronger in urban areas where pollution levels are higher.[2]

Thinking of reasons why the overall mortality rate as well as mortality for specific types of death could differ between urban and rural areas is not difficult. As just suggested, more air pollution in cities could contribute to respiratory and related problems (Calderon-Garciduenas et al. 2015; Zhou et al. 2015; Heutel and Ruhm, 2013), especially in infants (Currie and Schmieder, 2009; Foster, Gutierrez, and Kumar, 2009; Currie and Neidell, 2005; Chay and Greenstone, 2003). Similarly, the higher number of vehicles in metropolitan areas adds to traffic accidents and motor vehicle fatalities (French and Gumus, 2014). We consider in this paper whether associations between mortality and the business cycle also differ between urban and rural areas. We do find substantial differences in mortality rates between urban and rural settings, especially for women but no difference for African-Americans and young children. We also find significant differences regarding deaths due to heart disease as these deaths are more pro-cyclical in urban areas. External causes of death such as accidents are found to be more pro-cyclical in rural counties.

This analysis could be especially enlightening when comparing findings from individual-level studies that often find that being unemployed raises mortality for individuals. See Winkleman and Winkleman (1998), Burgard et al. (2007), Sullivan and Wachter (2009), Strully (2009) and Gradados at al. (2014). Job loss can be associated with depression, greater risks of disease, and deviant behaviors that diminish health and income thereby increasing mortality. An explanation to reconcile these contrasting views is that relatively few people become unemployed during a recession as an increase in the unemployment rate from 5% to 9%, for

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[2] Davis et al. (2010) find that emissions of particulate matter from trucking at the county-level in New Jersey were higher during economic booms.

example, still only directly impacts a minority of the labor force. So even if the newfound unemployed suffer greater mortality, overall mortality could still decrease if the slowing economy lowers pollution levels (which affects all residents) or lowers stress at work (for the majority who remain employed) as people find themselves less busy. Therefore, examining differences between rural and urban areas can help narrow explanations for the macroeconomic associations reported above.

The remainder of the paper is organized as follows: Section 1.2 describes the data and section 1.3 presents the methodology. Section 1.4 provides results and Section 1.5 concludes.

1.2 DATA

Our sample spans the 24 years from 1990 to 2013 and includes three recessions: 1990-91, 2001, and 2007-09. Data come from primary three sources: (a) Bureau of Labor Statistics (BLS), (b) Compact Mortality Files (CMF), and Environmental Protection Agency (EPA). Data of county unemployment rates come from Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS) in the U.S. Department of Labor.[3] Data on unemployment before 1990 is not compatible with subsequent data and the BLS cautions using them together. The unemployment rate we use corresponds to U-3 (the official unemployment rate) and is calculated as the number of unemployed people as a percentage of the labor force. To be unemployed, one must not have a job or be self-employed, actively seeking work and able to work. Data on mortality comes from Compact Mortality Files (CMF) of the National Center for Health Statistics (NCHS) in the Center for Disease Control and Protection (CDC) – CDC WONDER (Wide-ranging Online Data for Epidemiologic Research).[4] The CMF is a detailed

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[3] Data link: http://www.bls.gov/lau/
[4] Data link: http://wonder.cdc.gov/mortsql.html

databank that has information for the death of every U.S. resident including race, sex, census region, year of death, and cause of death (although see Appendix A for how the codes as to the cause of death have changed during our sample period). It also has data for population demographics. Unless otherwise stated, all mortality rates used here are crude rates that are calculated as the number of deaths per 100,000 people. Last but not the least, the pollution data used later in this paper come from United States Environmental Protection Agency (EPA).[5]

Finally, we discuss how we classify counties.[6] Metropolitan and micropolitan statistical areas, collectively known as Core Based Statistical Areas, are geographic entities delineated by the Office of Management and Budget (OMB) for use by Federal statistical agencies in collecting, tabulating and publishing Federal statistics. The OMB defines counties with more than 50,000 people to be metropolitan. Of the total 3,143 counties in the United States, 1,121 (36%) are classified as metropolitan counties and the rest as non-metropolitan ones although we will use the more simple terms "urban" and "rural". Alternatively, we also experiment with a different classification where the urban-rural threshold is 100,000 people.

Table 1.1 provides the means and standard deviations of the data. Of note is that mortality is higher in rural counties whether one considers overall mortality rates, rates for specific subpopulations, or rates for specific causes of death. Standard deviations are also higher. Given differences in these distributions we find it plausible that other characteristics between urban and rural areas could also differ, including associations between mortality and the business cycle.

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[5] Data link: http://www3.epa.gov/airdata/ad_rep_aqi.html

[6] Source link: http://www.bls.gov/oes/current/msa_def.htm

Table 1.1: Summary Statistics

Variables	All Counties Mean	All Counties S.D.	Urban Mean	Urban S.D.	Rural Mean	Rural S.D.
Overall Mortality Rate						
Mortality	1019.3	272.1	876.9	230.2	1099.9	260.7
Male Mortality	1050.0	296.9	899.5	249.4	1136.5	287.3
Female Mortality	997.7	285.1	857.4	232.0	1079.0	281.4
Whites Mortality	1054.4	286.7	909.3	245.3	1137.1	275.5
Blacks Mortality	888.8	407.3	768.7	343.8	1042.1	430.1
Age-Specific Mortality Rate						
Infants	859.3	367.3	804.4	300.6	1270.4	526.0
Under 5	205.7	91.6	189.1	72.9	294.6	124.2
Young Age (20-44)	177.9	77.6	153.1	59.0	202.1	85.6
Middle Age (45-64)	743.9	224.8	685.0	192.4	782.9	235.9
Old Age (65+)	5065.0	805.3	4949.4	697.6	5130.8	853.6
Over 85	15602.4	2748.5	15410.1	2262.7	15717.4	2995.8
Cause-Specific Mortality Rate						
Malignant Neoplasms	235.6	67.6	207.8	56.0	252.7	68.4
Metabolic Diseases	42.6	20.6	35.2	15.3	51.2	22.6
Nervous Diseases	47.0	27.6	38.4	21.8	57.5	30.1
Circulatory Diseases	393.4	141.8	326.5	112.9	432.8	142.3
Respiratory Diseases	106.1	42.1	87.2	30.4	119.5	44.1
Digestive Diseases	36.7	14.5	31.4	10.5	43.3	15.9
Genitourinary Diseases	25.9	13.5	21.2	9.7	34.3	15.0
External Causes of Death	75.1	30.2	63.1	21.8	84.9	32.5
Liver & Cirrhosis	15.3	8.6	13.3	5.5	23.3	12.9
Influenza & Pneumonia	33.6	21.7	25.8	13.7	44.4	25.7
Vehicle Accidents	24.7	15.8	18.8	10.6	34.9	18.0
Suicides	14.6	6.9	13.0	4.9	21.0	9.8
Independent Variables						
County Unemployment	6.3	3.0	5.9	2.6	6.5	3.1
State Unemployment	5.7	1.9	5.8	1.9	5.6	1.8
Average Population	90767	294877	211500	468823	23669	22919
Percent of Whites	87.8	16.2	86.1	14.4	88.7	17.0
Percent of Blacks	10.1	15.1	11.2	13.9	9.4	15.8
Percent of Infants	1.3	0.3	1.3	0.3	1.3	0.3
Percent of Under 5	6.5	1.2	6.7	1.1	6.3	1.2
Percent of 65+	15.2	4.3	13.1	3.7	16.4	4.1

Note: Mortality rate is calculated as the number of deaths per 100,000 population.

1.3 METHODOLOGY

To analyze the impact of cyclical fluctuations upon mortalities across urban and rural counties, we relate the natural log of j^{th} type mortality rate in county i at time t (H_{it}^{j}) to the annual county unemployment rate (UR_{it}) and several county-year demographic control variables (X_{it}) along with time-invariant county fixed effects (α_i), county-invariant time fixed effects (θ_t) and an error term (ε_{it}).

$$H_{it}^{j} = \alpha_i + \theta_t + \beta * UR_{it} + \gamma * X_{it} + \varepsilon_{it} \tag{1}$$

The coefficient of interest in equation (1) is β. It captures the impact of changes in the county unemployment rate on the mortality rate. The inclusion of fixed effects captures time-invariant unobserved characteristics of counties such as location and geography whereas time fixed effects control for variations across years that are consistent across counties such as the presence of a national recession or changes in government policies at the national level. The control variables include race-specific and age-specific demographic characteristics of the county such as the percentages of the county population who are white, African American, under five, and over sixty-five, respectively.

We consider two approaches. In the first approach, we estimate (1) separately for urban and rural counties and compare coefficients. In the second approach, we add an interactive term to (1) so that the new equation becomes:

$$H_{it} = \alpha_i + \theta_t + \beta * UR_{it} + \gamma * X_{it} + \delta * D * UR_{it} + \varepsilon_{it} \tag{2}$$

where D is a dummy that equals one for urban counties and zero for rural ones. The advantage of the second approach is that the sample size is greater as all counties are simultaneously considered. However, a disadvantage is that the coefficients upon X are restricted to be the same between urban and rural counties.

Notwithstanding, there are some weaknesses of our methodology. The first concerns the use of county level data. People are more likely to work and live in separate counties as opposed to separate states since crossing state lines always implies crossing county lines as well. Therefore, a mismatch between where people work and live is always a greater concern when using county level data. Another issue is the distinction between metropolitan and non-metropolitan counties. For our analysis, we use the most recent OMB classification of counties which is based on the number of people living in a county. Some counties that were non-metropolitan at the beginning of our sample later became metropolitan due to overall population growth pushing the county above the 50,000 threshold. We can deal with this issue by dropping such cases from our sample and comparing those metropolitan and nonmetropolitan counties that remained consistent throughout the sample.

1.4 RESULTS

1.4.1 Baseline Results

Table 1.2 presents the estimates of equation (1) for all counties (column 1) and then for urban and rural counties separately (columns 2 and 3, respectively). The coefficient for the unemployment rate is twice that for urban counties, -0.18, than it is for rural ones, -0.09. Columns (4)-(6) replace the mortality rate with the number of deaths and so consider an absolute level of mortality instead of a rate. In general, findings hold as the association between mortality and unemployment is stronger in urban rather than rural counties. Of note is that the coefficients for many of the control variables also differ between urban and rural counties, suggesting that the model of equation (2) is overly restrictive since it constrains coefficients upon all of the control variables to be the same between urban and rural counties.[7] Because of this, we focus upon the results when estimating (1) separately for both urban and rural counties although we present the coefficient estimates for the unemployment rate variables from (2) in Appendix B.

Table 1.2: Fixed Effect Estimates: Total Mortality Rate

	Mortality Rate			**Mortality Level**		
	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
County UR	-0.0014***	-0.0018**	-0.0009*	-1.201***	-2.203***	-0.695
	(0.000)	(0.001)	(0.001)	(0.413)	(0.637)	(0.520)
White (%)	0.009***	0.015***	0.001	7.562***	11.176***	2.988
	(0.002)	(0.002)	(0.002)	(1.400)	(1.336)	(1.955)
Black (%)	0.012***	0.019***	0.004	10.510***	14.676***	5.690**
	(0.002)	(0.002)	(0.003)	(1.658)	(1.634)	(2.515)
Under 5(%)	0.008***	0.004	0.009***	10.69***	8.76***	11.32***
	(0.002)	(0.003)	(0.002)	(1.823)	(2.523)	(2.439)
Over 65(%)	0.039***	0.049***	0.034***	38.187***	42.199***	36.597***
	(0.001)	(0.002)	(0.002)	(1.405)	(1.477)	(1.839)
Constant	5.383***	4.608***	6.234***	-399.479***	-846.153***	101.690
	(0.183)	(0.193)	(0.210)	(137.700)	(133.090)	(193.139)
N	67,416	26,227	41,189	67,416	26,227	41,189
R Squared	0.58	0.65	0.56	0.60	0.68	0.56
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is natural logarithm of total mortality rate per 100,000 population, except in last 3 columns where it is measured in levels. All specifications include county and time fixed effects and controls for the percentage of county populations who are white and black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[7] To formally test this, we ran a specification from column (1) where every right hand side variable was included by itself as well as with an urban interactive term. Of the five right hand side interactive terms, four were statistically significant, suggesting that several of the coefficients differ between rural and urban counties.

1.4.2 Demographic Subgroups

The top panel of Table 1.3 repeats the results of Table 1.2 to ease comparison but then considers various subgroups. The second and third panels of Table 1.3 consider males and females. The estimates suggest a bigger decline in female mortality when the county unemployment rate increases. In fact, the decline in the male mortality rate when the unemployment rate increases is almost similar between urban and rural counties, but the coefficient upon the unemployment rate for female mortality rate in urban counties is more than double the magnitude of the decline in rural areas. Furthermore, the female coefficient for unemployment (0.26) is almost twice the size of its male counterpart (0.14) in urban areas. These results suggest that mortality is most strongly pro-cyclical for urban females.

What can explain these differences in gender? For one, women more often than men visit the doctor and use medical services.[8] See Ashman et al. (2015) and Brett and Burt (2001). So during a recession, even when the opportunity cost of seeing a doctor falls fewer men do so and so their utilization of health care services is less dependent upon the state of the business cycle. Second, urban settings have more health care facilities and more specialists and so seeking medical treatment is more convenient than in rural areas. Therefore, the strongest associations for urban women could be due to women's greater willingness to seek medical treatment (relative to men) and the greater opportunity within urban settings to find it (relative to rural ones).[9] A third possibility relates to pollution. Chen et al. (2005) report that air pollution

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[8] Ruhm (2000) reports that routine checkups and preventative care goes down during recessions. Nevertheless, it could still be the case that people could be more likely to put off treatment for "nagging" ailments, believing problems to be minor, during busier economic booms.

[9] However, Ashman et al. (2015) reports little difference between boys and girls under the age of 18 which makes sense given a greater concern for a child's health regardless of gender than one's own health. Little difference also arises between elderly men and women in medical utilization rates.

increases mortality in women but no strong evidence links air pollution to fatal coronary heart disease in men. Women are also more likely to die of cardiovascular heart disease than are men. Therefore, the decline in pollution that occurs during recessions could benefit women more than men and could be most relevant in urban areas, where pollution levels are generally higher. We will consider this last explanation at greater length shortly.

Table 1.3: Results by Gender and Ethnicity

	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(5)**
County UR	-0.0014***	-0.0018***	-0.0009*	-1.201***	-2.203***	-0.695
	(0.000)	(0.001)	(0.001)	(0.413)	(0.637)	(0.520)
N	67,416	26,227	41,189	67,416	26,227	41,189
Male Mortality Rate and Level						
County UR	-0.0011**	-0.0014*	-0.0010*	-1.080**	-1.665**	-1.097*
	(0.000)	(0.001)	(0.001)	(0.487)	(0.766)	(0.611)
N	67,127	26,205	40,922	67,127	26,205	40,922
Female Mortality Rate and Level						
County UR	-0.0020***	-0.0026***	-0.0006	-1.418***	-2.753***	-0.277
	(0.001)	(0.001)	(0.001)	(0.481)	(0.698)	(0.608)
N	66,979	26,182	40,797	66,979	26,182	40,797
White Mortality Rate and Level						
County UR	-0.0008*	-0.0014*	-0.0002	-0.787*	-2.021***	0.141
	(0.000)	(0.001)	(0.001)	(0.468)	(0.715)	(0.596)
N	67,189	26,224	40,965	67,189	26,224	40,965
Black Mortality Rate and Level						
County UR	0.0014	0.0015	0.0017	1.824*	0.952	2.458*
	(0.001)	(0.002)	(0.001)	(1.034)	(1.348)	(1.478)
N	31,335	17,556	13,779	31,335	17,556	13,779

Notes: Dependent variable is the natural logarithm of total, male, female, white, and black mortality rate per 100,000 population, except in last 3 columns where it is measured in levels. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white, black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The last two panels report estimates of model (1) using race-specific mortality rates. Differences between whites and blacks are stark. Specifications (1)-(3) in the fourth panel suggest that, ceteris paribus, for a one percentage point increase in the county unemployment rate the white mortality rate falls by 0.14 and 0.02 in urban and rural counties, respectively. This shows that the decline in urban white mortality rate is 7 times more than the decline in its rural counterpart. However, a one percentage point increase in the county unemployment rate is associated with increases of 0.15 and 0.17 in urban and rural counties, respectively, for African-Americans. These are not statistically different from zero nor do they differ between the two types of counties. Fontenla et al. (2007) also report a similar distinction between blacks and whites as to how mortality changes across the business cycle. One possible explanation is that the unemployment rate of African Americans is almost twice as high as that of whites (U.S. Department of Labor)[10] and so county-level unemployment measures (aggregated across all ethnic groups) are less relevant for blacks. A further difference between blacks and whites that we find is the lack of any distinction between rural and urban counties for African-Americans.

We next consider different age groups. Following the literature and, specifically, Ruhm (2000), we consider three classifications: young (20-44), middle (45-64), and old ($\geq$ 65).[11] Obviously, the labor force will contain mostly young or middle-aged individuals. Table 1.4 reports parameter estimates of model (1) for these age-specific categories. For both the young and middle-aged, mortality is pro-cyclical. However, it is most strongly pro-cyclical for the young in rural counties. What is a possible explanation? The young are generally less likely to

[10] For details, visit: http://www.dol.gov/wb/stats/unemployment_sex_race_hisp_2014_txt.htm

[11] The mortality of infants and under-5 children did not show any differences across the business cycle which could be because of the availability of government programs to support them regardless of whether the economy is in recession or expansion.

seek regular medical treatment due to a lack of insurance or because they are confident in their overall health, especially if it means taking time off from work. Therefore, they forgo regular checkups and more so during economic booms, especially in rural areas where travel times to a doctor or specialist could be extensive. An undetected problem could suddenly surface resulting in death.

Table 1.4: Results by Age

	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Young (20-44 Year Old) Mortality Rate and Level						
County UR	-0.0055***	-0.0017	-0.0049***	-1.406***	-0.647*	-1.327***
	(0.001)	(0.002)	(0.001)	(0.260)	(0.352)	(0.346)
N	45,401	22,581	22,820	45,401	22,581	22,820
Middle-Aged (45-64 Year Old) Mortality Rate and Level						
County UR	-0.0023***	-0.0020*	-0.0010	-1.186**	-1.327	-0.326
	(0.001)	(0.001)	(0.001)	(0.510)	(0.870)	(0.627)
N	63,002	25,861	37,141	63,002	25,861	37,141
Old Age (≥ 65 Year Old) Mortality Rate and Level						
County UR	-0.0006	-0.0023***	0.0003	-3.601*	-11.640***	0.769
	(0.000)	(0.001)	(0.001)	(1.942)	(3.482)	(2.368)
N	67,282	26,209	41,073	67,282	26,209	41,073

Notes: Dependent variable is the natural logarithm of 20-44 year old (young), 45-64 year old (middle-aged), and 65 and over (old) mortality rate per 100,000 population, except in last 3 columns where it is measured in levels. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white, black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Across all counties (column 1), mortality is not strongly related to the business cycle for the elderly. The lack of any strong association is not surprising since incomes and medical care for the elderly fluctuate less over the business cycle due to Social Security and Medicare. Nevertheless, mortality for those over 65 is pro-cyclical in urban areas.[12] In urban settings senior citizen mortality is strongly pro-cyclical. Some elderly do work and the reason that they do so

[12] Results are similar when considering the mortality of those 85 and up.

could be because of a high opportunity cost of not working. Perhaps labor income is needed to augment retirement income in order to obtain basic necessities. In such cases, the opportunity cost of missing work could be high. During recessions, they work less and so more greatly utilize medical services. However, increased utilization could be greater in urban areas since there are more medical providers. Hence, the association between the business cycle and mortality becomes more pro-cyclical. A second possibility goes back to pollution. Pollution falls during recessions and the lower pollution levels in cities could lower mortality rates of the elderly, another group that is more susceptible to having heart problems due to air pollution. See Simoni et al. (2015).

1.4.3 Causes of Mortality

So far, we have considered mortality regardless of cause. We now consider mortality due to specific causes. As per the ninth revision of International Classification of Diseases (ICD-9), the major causes of mortality are classified into seventeen broad categories. The list of these causes is available in the appendix (although data is not available for all counties and so we limit our analysis to the 12 causes listed). We consider the following: (1) neoplasms/cancer, (2) circulatory / cardiovascular system diseases, (3) respiratory system diseases, (4) digestive system diseases, (5) genitourinary system diseases, (6) nervous system diseases, (7) nutritional and metabolic diseases, (8) aggregate external causes of death (9) chronic liver diseases, (10) motor vehicle accidents, (11) influenza and pneumonia, and (12) suicides.[13] These causes account for

[13] Diseases related to respiratory system consists of all the issues that are related to organs that are concerned with breathing, transfer of oxygen, and exit of carbon dioxide. This group of diseases also include influenza, pneumonia, respiratory infections and so on. Diseases of the nervous system interfere with the transmission of signals between different parts of the body or the coordination of voluntary and involuntary actions. Diseases related to digestive system consists of all the issues that are related to organs that are concerned with the breakdown and

the majority of deaths in the United States and they represent different aspects of physical and mental health as well as natural and non-natural types of mortality. Some of these categories represent mortalities due to long term illnesses such as malignant neoplasms, diseases of circulatory and respiratory systems, diseases of liver and cirrhosis, and so on while others represent mortalities due to short term incidents such as motor vehicle accidents. Although the transitory cyclical fluctuations proxied by annual county unemployment rate are more suitable for explaining variations in mortalities that occur due to short term rather than long term illnesses, we consider both in order to provide better comparisons and because the business cycle could worsen conditions even if it does not trigger the onset of the disease.

As shown in Tables 1.5 and 1.6, a great variety in results arises. For eight of these twelve specific causes of mortality, mortality is higher when unemployment is lower. The pro-cyclicality of heart related deaths could be caused by increased stress at work. The CDC acknowledges evidence linking work-related stress to heart disease. Heavy lifting in occupational settings can also result in an increased risk of a heart attack.[14] The extent that people work harder during economic booms then could cause a negative association between unemployment and mortality. Moreover, to the extent that urban settings cause more stress then associations should be stronger for urban counties. Pollution has also been linked to heart disease and decreasing pollution during recessions could then lower mortality.[15]

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digestion of food. Disease of nutritional and metabolic diseases include among others all types of diseases that are related to nutrition and food such as diabetes and vitamin deficiencies. Genitourinary system diseases are the ones related to reproductive organs and the urinary system.

[14] See www.cdc.gov/niosh/heartdisease/

[15] Visit: http://www.who.int/mediacentre/news/releases/2014/air-pollution/en/

Table 1.5: Results by Disease Type

	All	Urban	Rural	All	Urban	Rural
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
			Heart / Circulatory System Diseases			
County UR	-0.0031***	-0.0057***	-0.0016**	-0.522**	-1.727***	-0.565*
	(0.001)	(0.001)	(0.001)	(0.246)	(0.381)	(0.306)
N	66,392	26,133	40,259	66,392	26,133	40,259
			Neoplasms / Cancer			
County UR	0.0001	0.0003	0.0007	0.094	-0.054	0.278*
	(0.001)	(0.001)	(0.001)	(0.123)	(0.167)	(0.161)
N	65,057	26,013	39,044	65,057	26,013	39,044
			Influenza and Pneumonia			
County UR	-0.0096***	-0.0074**	-0.0081***	-0.161**	-0.064	-0.271***
	(0.002)	(0.003)	(0.003)	(0.068)	(0.086)	(0.104)
N	30,564	17,924	12,640	30,564	17,924	12,640
			External Causes of Death			
County UR	-0.0031***	0.0007	-0.0050***	-0.446***	-0.125	-0.562***
	(0.001)	(0.002)	(0.001)	(0.093)	(0.143)	(0.120)
N	52,796	23,874	28,922	52,796	23,874	28,922
			Vehicle Accidents			
County UR	-0.0121***	-0.0113***	-0.0096***	-0.228***	-0.187***	-0.252***
	(0.002)	(0.002)	(0.002)	(0.040)	(0.050)	(0.061)
N	26,942	17,105	9,837	26,942	17,105	9,837
			Liver and Cirrhosis			
County UR	-0.0002	-0.0004	-0.0037	-0.096**	-0.063*	-0.168
	(0.002)	(0.002)	(0.004)	(0.047)	(0.035)	(0.122)
N	15,893	12,743	3,150	15,893	12,743	3,150

Notes: Dependent variable is the natural logarithm of cause-specific mortality rate per 100,000 population, except in last 3 columns where it is measured in levels. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white, black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Likewise, mortality due to influenza could be increased due to not seeing a doctor as quickly during economic booms since the opportunity cost of missing work could be higher. Nevertheless, little difference arises between urban and rural settings. Results for cancer are acyclical. The lack of any positive or negative correlation with the business cycle could be due to a longer horizon. Consider heart problems as a contrast. Although heart problems could span years, they could be ignored until the onset of a heart attack comes suddenly. Likewise, coming down with a serious case of the flu could also happen suddenly. On the other hand, a cancer diagnosis often precedes death by months if not years.

Table 1.6: Results by Disease Type

	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Respiratory System Diseases						
County UR	0.0013	0.0022	0.0017	0.121	0.195	0.177
	(0.001)	(0.002)	(0.001)	(0.100)	(0.135)	(0.130)
N	57,847	24,706	33,141	57,847	24,706	33,141
Nervous System Diseases						
County UR	0.0057***	0.0029	0.0063**	0.254***	0.219*	0.339**
	(0.002)	(0.002)	(0.003)	(0.096)	(0.131)	(0.143)
N	35,531	19,536	15,995	35,531	19,536	15,995
Suicides						
County UR	0.0049***	0.0079***	-0.0037	0.035	0.072***	-0.079
	(0.002)	(0.002)	(0.003)	(0.028)	(0.027)	(0.071)
N	17,279	13,898	3,381	17,279	13,898	3,381
Digestive System Diseases						
County UR	-0.0016	-0.0028*	-0.0008	-0.112**	-0.104**	-0.099
	(0.001)	(0.002)	(0.001)	(0.044)	(0.051)	(0.063)
N	35,238	19,503	15,735	35,238	19,503	15,735
Nutritional & Metabolic Diseases						
County UR	0.0004	-0.0014	0.0025	-0.099	-0.119	0.014
	(0.002)	(0.002)	(0.002)	(0.072)	(0.091)	(0.105)
N	37,492	20,163	17,329	37,492	20,163	17,329
Genitourinary System Diseases						
County UR	-0.0037**	-0.0046*	-0.0040*	-0.128***	-0.111**	-0.149*
	(0.002)	(0.003)	(0.002)	(0.046)	(0.053)	(0.081)
N	26,314	16,777	9,537	26,314	16,777	9,537

Notes: Dependent variable is the natural logarithm of cause-specific mortality rate per 100,000 population, except in last 3 columns where it is measured in levels. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white and black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

External causes of death cover vast categories of fatalities such as poisoning, accidental falls, accidents caused by fire, submersion, suffocation, surgical and medical procedure mishaps, suicides, homicides, terrorism, deaths caused by environmental factors, and so on. Since this category is an amalgam of many different causes of death, we will focus on some of them specifically in addition to others such as motor vehicle accidents and suicides. External causes of death are found to be pro-cyclical but only for rural counties. One explanation is that many dangerous occupations occur in rural areas such as lumbering, mining, and farming and the number of occupational accidents decrease when fewer people work during recessions. See Radeloff et al. (2005). Vehicle accidents are pro-cyclical in both types of counties.

Not surprisingly, suicides are countercyclical but our results show that this holds true mainly for urban counties. Perhaps rural settings provide more supportive environments that help to deter their occurrence. Diseases of the nervous system are also countercyclical but only for rural counties. See Sokejima and Kagamimori (1998). Diseases of the respiratory system appear to be acyclical. This seems to contradict changing pollution levels as an explanation of our findings. However, a death due to lung disease is likely to be less sudden than one due to a heart attack, for example. This difference in timing could then weaken the correlation between unemployment and mortality due to respiratory causes. Digestive system diseases are procyclical but mostly for urban counties whereas genitourinary system diseases are pro-cyclical in both.

1.4.4 100,000 Threshold

The above analysis considers a 50,000 person threshold distinguishing rural from urban counties. One can also consider other thresholds, such as 100,000.[16]

[16] Results using higher thresholds are similar.

Table 1.7: 50,000 and 100,000 Thresholds

Mortality Rate	**All Counties**	**Under 50K**	**50K-100K**	**Over 100K**
All Mortality Rate	-0.0014***	-0.0009*	-0.0029**	-0.0009
	(0.000)	(0.001)	(0.001)	(0.001)
Male Mortality Rate	-0.0011**	-0.0010*	-0.0021*	-0.0007
	(0.000)	(0.001)	(0.001)	(0.001)
Female Mortality Rate	-0.0020***	-0.0010	-0.0038***	-0.0014
	(0.001)	(0.001)	(0.001)	(0.001)
White Mortality Rate	-0.0008*	-0.0002	-0.0027**	-0.0006
	(0.000)	(0.001)	(0.001)	(0.001)
Black Mortality Rate	0.0014	0.0017	0.0066**	0.0018
	(0.001)	(0.001)	(0.003)	(0.002)
20-44 Year Old Mortality Rate	-0.0055***	-0.0049***	-0.0073***	0.0038*
	(0.001)	(0.001)	(0.003)	(0.002)
45-64 Year Old Mortality Rate	-0.0023***	-0.0010	-0.0034**	-0.0006
	(0.001)	(0.001)	(0.002)	(0.001)
≥ 65 Year Old Mortality Rate	-0.0006	0.0003	-0.0015	-0.0015*
	(0.000)	(0.001)	(0.001)	(0.001)
Heart / Circulatory Diseases	-0.0031***	-0.0016**	-0.0048***	-0.0072***
	(0.001)	(0.001)	(0.001)	(0.001)
Neoplasms / Cancer	0.0001	0.0007	0.0002	0.0020***
	(0.001)	(0.001)	(0.001)	(0.001)
Influenza and Pneumonia	-0.0096***	-0.0081***	0.0035	-0.0132***
	(0.002)	(0.003)	(0.004)	(0.004)
External Causes of Death	-0.0031***	-0.0050***	-0.0076***	0.0090***
	(0.001)	(0.001)	(0.002)	(0.003)
Vehicle Accidents	-0.0121***	-0.0096***	-0.0096***	-0.0102***
	(0.002)	(0.002)	(0.003)	(0.003)
Liver and Cirrhosis	-0.0002	-0.0037	-0.0062*	0.0003
	(0.002)	(0.004)	(0.003)	(0.002)
Respiratory System Diseases	0.0013	0.0017	0.0021	0.0008
	(0.001)	(0.001)	(0.003)	(0.002)
Nervous System Diseases	0.0057***	0.0063**	-0.0012	0.0061**
	(0.002)	(0.003)	(0.004)	(0.003)
Suicides	0.0049***	-0.0037	-0.0051*	0.0103***
	(0.002)	(0.003)	(0.003)	(0.002)
Digestive System Diseases	-0.0016	-0.0008	0.0011	-0.0014
	(0.001)	(0.001)	(0.002)	(0.002)
Nutritional & Metabolic Diseases	0.0004	0.0025	0.0024	0.0032
	(0.002)	(0.002)	(0.003)	(0.003)
Genitourinary System Diseases	-0.0037**	-0.0040*	-0.0042	-0.0051*
	(0.002)	(0.002)	(0.004)	(0.003)

Notes: Dependent variable is the natural logarithm of various demographic mortality rate per 100,000 population. All specifications also include county and time FEs as well as controls for the percentage of county populations who are white and black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.7 presents four sets of results. The first two columns present results from previous tables to ease comparison. Column one presents coefficients estimates upon UR for all counties and column two for counties with less than 50,000 people which are the rural ones as previously classified. Column three presents results for those counties having between 50,000 and 100,000 whereas column four shows outcomes for those counties with at least 100,000 people. As before, counties with less than 50,000 people comprise about $5/7^{th}$ of the sample. Those in the middle group are a little less than $1/7^{th}$ of the total and the largest a little more than $1/7^{th}$. Some interesting findings emerge, some supportive of previous conjectures whereas others raise doubts.

First, the most negative coefficients for mortality due to circulatory diseases or influenza / pneumonia are for counties with more than 100,000 people, supporting conjectures that higher pollution levels during economic booms could be contributing to these events. Suicides are most countercyclical in these biggest counties, again suggesting that beneficial support networks might actually be less available in larger places. County size does not seem to matter in the case of deaths caused by vehicular accidents as the coefficients upon UR remain steady across the three columns.

However, some important differences also arise. Whereas external deaths are pro-cyclical in rural counties they are countercyclical in these largest counties. More importantly, consider the coefficients upon UR in the top rows, presenting results for these more general demographic categories. Not only are the coefficient estimates generally larger in magnitude for the 50,000 to 100,000 range (column 3) but they are often insignificant (column 4). If “bads” such as pollution impact women and the elderly more and this is what explains past results, then the largest coefficients (in magnitude) should be in these largest counties. A possible explanation is that the largest counties have the best medical resources to lower mortality and that this offsets some of the triggers of mortality that become more prominent in booms. The "medium-sized" counties on the other hand contain many of these same triggers of mortality but that medical quality is less effective at preventing deaths caused by these triggers.[17]

Table 1.8 presents additional summary statistics that can help distinguish mortality across these types of counties. First, mean unemployment is lowest in small counties but the within-county standard deviation is largest. The opposite is true for the largest counties. Moreover, both mean mortality and its within-county standard deviations decrease in more populous counties. So a possible explanation for the above findings is that rural counties can be so dissimilar that strong associations between unemployment and mortality are difficult to find. In essence, the signal to noise ratio is low. Larger counties, on the other hand, see less variation in mortality over time thereby again weakening associations between unemployment and mortality. Medium-sized counties denote a "goldilocks" case where noise does not overwhelm the signal which is less stable over time and so is more responsive to changing business cycle conditions.

Table 1.8: Summary Statistics across County Type

County	Less than 50,000		50,000 to 100,000		Over 100,000	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
UR	3.77	1.92	5.81	1.83	8.92	1.92
Mortality						
All	6.96	0.114	6.79	0.064	6.68	0.06
Males	6.99	0.142	6.81	0.074	6.69	0.067
Females	6.93	0.144	6.77	0.084	6.66	0.068
Over 65	8.53	0.133	8.51	0.075	8.47	0.071
44-65	6.61	0.189	6.53	0.118	6.44	0.106
20-44	5.26	0.213	4.98	0.189	4.89	0.158

[17] A cause for concern is that not all counties remain in one group across the entire sample period. Changes in population could cause a county to switch, for example, from rural to urban or from medium to large. However, such switching is not what is driving findings. The results of Table 1.6 are substantively unchanged when limiting the set of large counties to those that remained above 100,000 throughout the sample period.

1.4.5 Pollution

Although not always, many of the above results suggest that pollution could provide a possible explanation and, as stated, finding an explanation is not difficult as booming economies could create more pollution that then increases mortality. Heutel and Ruhm (2013) consider to what extent pollution is the explanation relating mortality to the business cycle. Although they focus upon state-level data, they conduct robustness checks using county-level data. When using county-level data, they find that inclusion of a measure of carbon monoxide weakens associations between unemployment and mortality. Although we have not so far measured pollution directly, our results did speak to theirs although not unambiguously. As stated above, we do find evidence suggesting that pollution plays some role in driving differences in association in urban versus rural counties. However, it also appears that other factors play a role, especially considering that associations weaken for counties exceeding 100,000. In this final subsection, we consider pollution more directly.

We present results for two types of pollution variables. The first is the one used by Heutel and Ruhm (2013). It measures pollution levels for PM10 (particulate matter at most ten micrograms in size) and ozone.[18] For each year, they average pollution levels at monitor stations within 20 miles of a county's population centroid, even if the station is not within the county itself. We also use a second set of measures, air quality indices (AQI) from the United States Environmental Protection Agency (EPA). AQI, ranging between 0 and 500, is like a yardstick which is used to measure the level of pollution in the air. The higher the AQI value, the greater the level of air pollution and the greater the health concern. These indices denote the number of days that the air quality index is above the threshold level of the national average as well as the

[18] Heutel and Ruhm (2013) also include carbon monoxide as one of the pollution variables but data is less available for this pollutant, thereby greatly reducing the sample size.

AQI score at the 90th percentile. An AQI value of 100 generally corresponds to the national air quality standard for the pollutant and air with AQI value above 100 is considered unhealthy.

Table 1.9: Mortality, Unemployment and Pollution

Type	**Total**	**Female**	**Age ≥ 65**	**Circulatory**	**Respiratory**	**Influenza**
Panel A: Baseline Coefficients upon UR						
County UR	-0.0018**	-0.0026***	-0.0023***	-0.0057***	0.0022	-0.0074**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Panel B: Coefficients for UR and AQI_{90}						
County UR	-0.0031**	-0.0045***	-0.0022*	-0.0028	0.0008	0.0019
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)
AQI_{90}	-0.0001	-0.0001	-0.0001	0.00004	-0.0003	-0.0004
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Coefficients for UR and AQI_{NOD}						
County UR	-0.0030**	-0.0044***	-0.0021	-0.0028	0.0007	0.0019
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)
AQI_{NOD}	0.00001	0.00002	0.00001	0.00003	-0.00009	-0.00007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel D: Coefficients for UR and PM_{10} and O_3						
County UR	-0.0023**	-0.0032**	-0.0007	-0.0043***	0.0020	0.0021
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
PM_{10}	-0.0019***	-0.0021***	-0.0015	-0.0019	-0.0024	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
O_3	-0.2460	-0.3070	0.0358	-0.4463	0.2534	1.4786
	(0.560)	(0.701)	(0.686)	(0.740)	(1.564)	(2.397)

Notes: Dependent variable is the natural logarithm of mortality rate per 100,000 population for total, female, 65 and over (old), circulatory system disease, respiratory system disease, and influenza. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white, black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results are given in Table 1.9 but only for those types of mortality that the results above suggest could be most sensitive to pollution levels: total, females, the elderly, circulatory disease, respiratory disease, and influenza. We do not include all the pollution variables simultaneously but consider them separately in the three panels of the tables. Moreover, we only present results for urban counties. Results for rural counties were insignificant which is not surprising given the above results and the lower levels of pollution in rural counties.

Panel A re-presents the above coefficient estimate on the unemployment rate so as to provide a basis of comparison. Panel B considers the unemployment rate and the AQI 90th percentile. Panel C shows the coefficients for the unemployment rate and the number of days that the AQI exceeded the aforementioned threshold. Finally, panel D presents coefficients for the unemployment rate and the Heutel and Ruhm (2013) measures. We include their measures together to more closely correspond to their specification.

Results are far from conclusive. For total and female mortality, the coefficients upon UR actually increase in magnitude whereas coefficients for the pollution variables are insignificant with the exception of PM_{10}. The greater magnitude for the UR coefficients suggests that controlling more pollution actually increases the pro-cyclical nature of mortality. However, it should also be noted that the coefficients upon unemployment are the same when the pollution variables are removed but restricting the sample to only those observations for which pollution data exists. In other words, it is not the inclusion of the pollution variables themselves that are increasing the magnitudes of the UR coefficients but the reduction in sample size caused by including the pollution variables. For the elderly, the coefficient upon UR stays steady (although significance levels vary) except when PM_{10} and O_3 are included. The biggest changes occur in the last three columns. The inclusion of the pollution variables lower the coefficients upon UR for these types of mortality. However, coefficients for the pollution variables are largely insignificant except for that upon PM_{10} when mortality due to heart or circulatory factors is considered.

1.5 CONCLUSION

Using fixed effects estimation for U.S. county level data covering a period of twenty-four years from 1990 to 2013, this study provides a nuanced story to the recent findings of the pro-cyclical behavior of mortality. We find that mortality declines in both rural and urban areas with an increase in the unemployment rate. However, the decline in urban mortality is double that of its rural counterpart when considering the total population. It is more than double when examining women and the elderly. Previous research has shown that both of these subgroups are more sensitive to pollution than is the population in general and so one explanation for these findings are that mortality declines as business conditions slow and less pollution is emitted. The stronger association between the unemployment rate and mortality in urban areas also holds for heart and other diseases of the circulatory system. Again, to the extent that higher pollution levels increase the prevalence and severity of these diseases then the stronger association found in urban areas is not surprising.

Nevertheless, some of our findings question rising pollution in boom times as a reason. First, why does a similar association not hold for African-Americans since they would also be affected by pollution? Moreover, our findings weaken once we use a 100,000 threshold to distinguish urban from rural counties. In a pollution-related story, results should be stronger as we raise the threshold. On the other hand, results remain strongest in these larger counties for circulatory and influence/pneumonia types of mortality, two types that are presumably more tied to pollution levels. Finally, using direct measures of pollution we did not find strong evidence that mortality rises with pollution levels.

If pollution is not a major reason, then what can explain the differences between urban and rural counties as to how mortality changes across the business cycle? Stronger economies could increase stress levels that are also more strongly felt in urban areas. It is also possible that weaker economies allow those who still have jobs more time to seek routine checkups and medical treatment and this is what explains our findings. However, the micro data is less supportive of this explanation, since such checkups and “routine” medical care fall during recessions. Our findings do show that the association between unemployment and mortality is strongest for medium-sized counties and we suggest that these areas could be what is driving the findings using state-level data. Further considering the characteristics of these counties in order to better explain results is a focus of future work.

Two exceptions, however, arise as to the stronger association between unemployment and mortality in urban areas. The first involves young workers. Presumably, they are generally less affected by stress and pollution, at least in the short run. Instead, an opportunity cost story could better suit them. With fewer routine visits, more severe issues could suddenly manifest. Their distance in rural areas from adequate medical facilities could then prove fatal. Second, external accidents are more pro-cyclical in rural settings. Such accidents could increase during economic booms as more occupational accidents occur and prove more fatal in rural areas as, again, distance from medical attention could be decisive. Moreover, many dangerous occupations also appear in rural settings.

The often-reported finding that mortality falls in recessions seems counterintuitive given the hardships that we often see with the unemployed and so finding explanations to reconcile such results is necessary. By considering how associations between unemployment and mortality differ between urban and rural counties, we hope to have narrowed the set of possibilities although we acknowledge that our findings also raise important questions. More work needs to be done to further pare down these possible explanations. We encourage such future examinations, especially considering the nuances that our findings suggest.

CHAPTER 2

ASYMMETRIES ACROSS THE BUSINESS CYCLE: A RE-EXAMINATION OF UNEMPLOYMENT'S IMPACT UPON MORTALITY

2.1 INTRODUCTION

Much research has considered how health in general and mortality in particular evolve across the business cycle. Ruhm (2000) considered a panel of U.S. states and found mortality rate to be pro-cyclical, that is, mortality declines during recessions as measured by the state unemployment rate. In other words, mortality and the unemployment rate were negatively associated. Later work reconsidered his findings using different countries or slightly different specifications. These studies include: Neumayer (2004) for Germany, Tapia Granados (2005) for Spain, Gonzalez and Quast (2010) for Mexico, Ariizumi and Schirle (2012) for Canada, Lin (2009) for Pacific Asian countries, and Gerdtham and Ruhm (2006) for OECD countries. The finding that mortality fell in recessions was surprising although such a claim was made over 90 years ago in Ogburn and Thomas (1922). However, exceptions also arise. Brenner (1973, 1975, and 1979) find that mortality is countercyclical. Moreover, many studies using family or individual level data such as Strully (2009), Halliday (2014), Sullivan and von Wachter (2009), Gerdtham and Johannesson (2005) Winkleman and Winkleman (1998), Burgard et al. (2007), and Gradados at al. (2014) find that job loss can be associated with depression, greater risks of disease, and deviant behaviors that diminish health and income thereby increasing mortality.

Several explanations have been considered as to why the mortality rate could be pro-cyclical even with the aforementioned findings of the negative effects of job loss. A first set of explanations consider how people respond to job loss or reductions in income. The opportunity cost of going to the doctor or of exercising and taking time to eat healthy is, presumably, higher during expansions than during recessions. Alternatively, people might push themselves harder during expansions such as work overtime or work multiple jobs. Such activities could cause more stress or allow them to become more susceptible to disease. During expansions people become wealthier and that might encourage them to take on risky activities such as excessive drinking or driving more recklessly thereby increasing fatality rates (Ruhm, 1995). In all of these cases, people's behavior changes across the business cycle and such changes hold ramifications for health in general and mortality, in particular.

More generally, income falls during recessions and rises during expansions. The impact of a fall in wages due to recessions can be classified into income and substitution effects with respect to the consumption of healthy goods such as exercise, medical treatment, and diet. The income effect suggests that a fall in income would induce reductions of these normal goods. However, a reduction in working hours would lower the opportunity cost of consuming healthy goods (especially exercise) and so increase their consumption via the substitution effect (Dehejia and Lleras-Muney, 2004). The micro-literature suggests the income effect is dominant whereas the macro-literature suggests greater importance of substitution effects.

A second possibility is that environmental factors change across the business cycle that affects even those who do not face changes in income. For example, pollution could cause more deaths during economic booms when production is higher. As the industrial production declines during recessions so does the pollution level which could contribute to the reduction of mortalities from heart disease and respiratory problems as explored by Heutel and Ruhm (2013).[19]

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[19] Davis et al. (2010) find that emissions of particulate matter from trucking at the county-level in New Jersey were higher during economic booms.

Because of the distinct findings in the association between mortality and unemployment when using macro-level data (county, state, or country) versus micro-level data (individual or household), reconciling the two becomes important. One way to do this is to consider more nuanced approaches. Our approach will consider two such nuances.

First, does the negative association between unemployment and mortality first found in Ruhm (2000) hold more strongly during economic booms or recessions? That is, do booms raise mortality or do recessions lower it?[20] Perhaps recessions have little effect upon mortality but strong economic expansions increase it. Or, perhaps recessions do, indeed, lower mortality but economic expansions have no effect at all thereby causing the effect of an economic downturn to be underestimated if one presumes a symmetric relationship. Despite these concerns, a common assumption in the literature has been that of symmetry. That is, the impact of rising unemployment upon mortality is considered to be of the same magnitude as the impact of falling unemployment. Consider the simplified model as an illustration.

$$Mortality = \alpha + \beta * Unemployment + \varepsilon \tag{1}$$

A one unit rise in unemployment is predicted to raise mortality by β whereas an opposite but equal change in unemployment is predicted to decrease mortality by β. However, this assumption of symmetry might not hold and researchers have considered many circumstances where it might not. Hamilton and Lin (1996) and Schwert (1989) find that stock return volatility is higher during recessions in comparison to expansions. Similarly, Kilian and Vigfusson (2011),

[20] Mocan and Bali (2010) consider crime across the business cycle. Although they find that property crime is asymmetrical they do not find statistical evidence of asymmetry for homicides / murder.

Hamilton (2011, 2003, and 1983) and Mork (1989) find that oil price shocks have asymmetric impacts on macroeconomic conditions in the United States. Chen (2007) finds that contractionary monetary policy seems to have much larger effects during bear-market periods than the effects during bull-market periods. Closer to our study, Mocan and Bali (2010) find that rising unemployment is more strongly associated with rising property crime than falling unemployment is associated with diminishing property crime.

Our second nuance will consider whether there are particular settings where this association between mortality and unemployment is stronger than in others? For instance, if the negative association is stronger in urban than in rural areas, then this could suggest that the explanation for these associations stems from factors more common to urban areas. Several examples quickly show how such differences could arise. Pollution might never be a factor in rural counties regardless of the state of the business cycle. More air pollution in cities could contribute to respiratory and related problems (Calderon-Garciduenas et al. 2015; Zhou et al. 2015; Heutel and Ruhm, 2013), especially in infants (Currie and Schmieder, 2009; Foster, Gutierrez, and Kumar, 2009; Currie and Neidell, 2005; Chay and Greenstone, 2003). This would suggest that associations between the business cycle and mortality would be stronger in cities. On the other hand, the opportunity costs of visiting doctors, especially specialists, could be much higher in rural counties since such practitioners could require hours of travel. Therefore, at the margin, changing business cycle conditions could have a much greater effect upon this opportunity cost of seeking routine medical care in rural counties. Professions such as logging, mining, and farming are more dangerous than most others, having higher mortality rates due to on-the-job accidents. Such professions are more commonly found in rural areas. Similarly, the higher number of vehicles in metropolitan areas adds to traffic accidents and motor vehicle fatalities (French and Gumus, 2014).

We will combine these two approaches, allowing different types of asymmetries in large versus small counties. But as stated, we also allow any asymmetries to differ depending upon the size of the county. Continuing with some of the above, pollution might never be a factor in rural counties regardless of the state of the business cycle. Instead, any asymmetry driven by pollution might only be found in large counties. Or suppose the association between the business cycle and mortality is driven by changing opportunity costs of seeking medical treatment across the business cycle. However, the opportunity costs of visiting doctors, especially specialists, could be much higher in rural counties since such practitioners could require hours of travel. Professions such as logging, mining, and farming are more dangerous than most others, having higher mortality rates due to on-the-job accidents. Such professions are more commonly found in rural areas. If changes in business cycle conditions mostly cause asymmetric effects upon mortality in these professions, then such asymmetries should be more strongly felt in smaller counties.

To better examine these issues and specifically distinctions between urban and rural settings, we will use county-level data since it will allow for a more refined analysis than state-level data would allow. Many rural areas can be found even in states as populous as California and Texas and so denoting observations from these states as “large” would incorrectly subsume these rural areas into this category. Of course, uniformity need not exist across counties either, but the degree of dissimilarities across counties is likely to be much smaller.[21] Another

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[21] We are not the first to apply county-level data to the issue of mortality and the business cycle. Fontenla, Gonzalez, and Quast (2011) focus on the race and ethnicity aspect of mortality and their results exhibit a pro-cyclical pattern of mortality for whites and Latinos but not for African-Americans.

disadvantage of county-level data is that reporting errors could be larger as such errors could be more frequent with less aggregated data as reported in Pierce and Denison (2006).

To the best of our knowledge, no past study has focused on any asymmetric association between business cycles and mortalities. This makes our research the first of its kind for explaining such an asymmetric relationship. Notwithstanding, this makes the job at hand more challenging as well since no specific econometric model can explain the issue of asymmetries thoroughly. We propose a variation of Mocan and Bali (2010) econometric specification. Using different county level mortality measures and unemployment rates accompanied by county-specific and time-specific fixed effects along with several control variables, we experiment with several econometric models that allow for different possible asymmetries.

The remainder of the paper is organized as follows: Section 2.2 describes the data and section 2.3 presents the methodology. Section 2.4 provides results and Section 2.5 concludes.

2.2 DATA

Our sample spans the 24 years from 1990 to 2013 and includes three recessions: 1990-91, 2001, and 2007-09. The data come from mainly two sources. Unemployment data at the county level comes from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS) in the U.S. Department of Labor.[22] LAUS provides monthly and annual employment, unemployment and labor force data for all the U.S. States, counties, census regions, metropolitan areas, and many more. Data on unemployment before 1990 is not compatible with subsequent data and the BLS cautions using them together. The unemployment rate we use is U-3, the official unemployment rate.

[22] Data link: http://www.bls.gov/lau/

Table 2.1: Summary Statistics

	All Counties		Urban		Rural	
Variables	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Overall Mortality Rate						
Mortality	1019.3	272.1	876.9	230.2	1099.9	260.7
Male Mortality	1050.0	296.9	899.5	249.4	1136.5	287.3
Female Mortality	997.7	285.1	857.4	232.0	1079.0	281.4
Whites Mortality	1054.4	286.7	909.3	245.3	1137.1	275.5
Blacks Mortality	888.8	407.3	768.7	343.8	1042.1	430.1
Age-Specific Mortality Rate						
Infants	859.3	367.3	804.4	300.6	1270.4	526.0
Under 5	205.7	91.6	189.1	72.9	294.6	124.2
Young Age (20-44)	177.9	77.6	153.1	59.0	202.1	85.6
Middle Age (45-64)	743.9	224.8	685.0	192.4	782.9	235.9
Old Age (65+)	5065.0	805.3	4949.4	697.6	5130.8	853.6
Over 85	15602.4	2748.5	15410.1	2262.7	15717.4	2995.8
Cause-Specific Mortality Rate						
Malignant Neoplasms	235.6	67.6	207.8	56.0	252.7	68.4
Metabolic Diseases	42.6	20.6	35.2	15.3	51.2	22.6
Nervous Diseases	47.0	27.6	38.4	21.8	57.5	30.1
Circulatory Diseases	393.4	141.8	326.5	112.9	432.8	142.3
Respiratory Diseases	106.1	42.1	87.2	30.4	119.5	44.1
Digestive Diseases	36.7	14.5	31.4	10.5	43.3	15.9
Genitourinary Diseases	25.9	13.5	21.2	9.7	34.3	15.0
External Causes of Death	75.1	30.2	63.1	21.8	84.9	32.5
Liver & Cirrhosis	15.3	8.6	13.3	5.5	23.3	12.9
Influenza & Pneumonia	33.6	21.7	25.8	13.7	44.4	25.7
Vehicle Accidents	24.7	15.8	18.8	10.6	34.9	18.0
Suicides	14.6	6.9	13.0	4.9	21.0	9.8
Independent Variables						
County Unemployment	6.3	3.0	5.9	2.6	6.5	3.1
State Unemployment	5.7	1.9	5.8	1.9	5.6	1.8
Average Population	90767	294877	211500	468823	23669	22919
Percent of Whites	87.8	16.2	86.1	14.4	88.7	17.0
Percent of Blacks	10.1	15.1	11.2	13.9	9.4	15.8
Percent of Infants	1.3	0.3	1.3	0.3	1.3	0.3
Percent of Under 5	6.5	1.2	6.7	1.1	6.3	1.2
Percent of 65+	15.2	4.3	13.1	3.7	16.4	4.1

Note: Mortality rate is calculated as the number of deaths per 100,000 population.

Data on mortality comes from Compact Mortality Files (CMF) of the National Center for Health Statistics (NCHS) in the Center for Disease Control and Protection (CDC) – CDC WONDER (Wide-ranging Online Data for Epidemiologic Research).[23] The CMF is a detailed databank that has information for the death of every U.S. resident including race, sex, census region, year of death, and cause of death.

It also has data for population demographics, used as control variables in our model. The sample period spans two revisions of the International Classification of Diseases (ICD) codes for the underlying causes of death - ICD-9 and ICD-10, produced by the World Health Organization (WHO). ICD-9 codes are used during 1979-1998 whereas ICD-10 codes are used during 1999-present.[24,25] In order to provide a reasonable comparison among these codes, NCHS employed comparability ratios based on the relative number of cause-specific deaths in 1976 for reconciling ICD-8 and ICD-9 classifications (Ruhm, 2013; Klebba and Scott, 1980) and in 1996 for reconciling ICD-9 and ICD-10 classifications (Anderson et al., 2001). Summarized lists of these ICD codes are reported in Tables 1A and 2A in the appendix. It is worth mentioning that unless otherwise stated, all mortality rates we use are calculated as the number of deaths per 100,000 people.

Table 2.1 provides the means and standard deviations of the data. In addition to providing these summary statistics, it also presents mortality rates when splitting the sample into urban and rural counties (using the Office of Management and Budget defined threshold of 50,000 people to distinguish the two). One clearly sees different mortality rates between the two groups.

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[23] Data link: http://wonder.cdc.gov/mortsql.html

[24] For details, go to: http://www.icd9data.com/2015/Volume1/

[25] For details, visit: http://www.icd10data.com/ICD10CM/Codes

Therefore, it is possible that mortality also differs in other ways between the two as well, including in how it evolves across the business cycle.

2.3 METHODOLOGY

In contrast to the standard static mortality models, we define mortality rate as an asymmetric function of the unemployment rate where the conditional mean of the mortality rate is defined to follow two different paths depending upon whether there has been an increase or decrease in the unemployment rate. Our model of estimation includes the natural log of mortality rate in county i at time t (M_{it}) in relation to increase (UR_{it}^{+}) and decrease (UR_{it}^{-}) in the county unemployment rate and several county-year demographic control variables (X_{it}) along with time-invariant county fixed effects (α_i), county-invariant time fixed effects (θ_t) and the regression error term (ε_{it}).

$$M_{it} = \alpha_i + \theta_t + \beta UR_{it}^{+} + \delta UR_{it}^{-} + \pi(POP_{it}UR_{it}^{+}) + \mu(POP_{it}UR_{it}^{-}) + \gamma X_{it} + \varepsilon_{it} \qquad (2)$$

Both year and county fixed effects are included in the specification. The inclusion of fixed effects captures time-invariant unobserved characteristics of counties such as location and geography whereas time fixed effects control for variations across years that are consistent across counties such as the presence of a national recession or changes in federal government policies. Matrix X_{it} includes county-level, time varying demographic variables such as the percentage of whites, the percentage of African-Americans, the percentage of people under five years of age, and the percentage of people aged 65 and above. The natural log of the county population is also included in X_{it} as well as in the interactive terms. Following Mocan and Bali (2010), we define the variables UR_{it}^{+} and UR_{it}^{-} as:

$$UR_{it}^{+} = UR_{it} \;\; if \;\; UR_{it} \geq UR_{it-1} \;\; and \;\; = \;\; 0, \;\; otherwise \qquad (3)$$

$$UR_{it}^{-} = UR_{it} \;\; if \;\; UR_{it} < UR_{it-1} \;\; and \;\; = \;\; 0, \;\; otherwise \qquad (4)$$

So, we allow increases in the unemployment rate to have different effects upon mortality as do decreases in which case: $\beta + \pi \neq \delta + \mu$. This asymmetry exists even if $\pi = \mu = 0$ although county size would not impact the influence that unemployment has upon mortality.

2.4 RESULTS

2.4.1 Baseline Results

Table 2.2 presents the estimates of equation (2) but first restricts some of the coefficients to be zero so as to begin with a more parsimonious model. The first column is the most simplistic linear model that suggests pro-cyclicality of mortality as found in the previous literature. The second column does not even allow for any asymmetry nor does it allow the coefficient upon *UR* to vary along with county size. The coefficient upon *UR* is negative but not significant. Unlike many of the aforementioned studies, no strong evidence arises that mortality is pro-cyclical when population is incorporated to the model. The coefficient upon *POP* is negative and strongly significant. Mortality is lower in larger counties. This result could stem from the better and nearer medical facilities found in more populous areas. Column 3 does not allow for asymmetries but does allow the coefficient upon *UR* to differ with the natural log of the population. The coefficient upon *UR* is now -0.64 + 0.06**POP*. Mortality is pro-cyclical but only for small counties. The coefficient becomes positive for a value of *POP* around ten (which denotes a population level of around 22,000).

Table 2.2: Fixed Effects Estimates: Baseline Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
UR	-0.138***	-0.047	-0.637***			
	(0.042)	(0.042)	(0.235)			
POP		-15.33***	-15.85***	-16.02***	-17.17***	-15.06***
		(1.174)	(1.186)	(1.231)	(1.386)	(1.235)
POP*UR			0.057***			
			(0.021)			
UR+				-0.643***	-0.613**	0.291
				(0.235)	(0.248)	(0.401)
UR-				-0.896***	-0.980***	0.377
				(0.259)	(0.266)	(0.452)
POP*UR+				0.057***	0.052**	-0.032
				(0.021)	(0.023)	(0.037)
POP*UR-				0.083***	0.089***	-0.039
				(0.024)	(0.024)	(0.042)
White (%)	0.857***	0.584***	0.608***	0.617***	0.635***	0.473***
	(0.187)	(0.149)	(0.151)	(0.162)	(0.162)	(0.158)
Black (%)	1.203***	0.923***	0.936***	0.979***	1.016***	0.672***
	(0.211)	(0.171)	(0.173)	(0.185)	(0.187)	(0.183)
Under 5 (%)	0.777***	0.826***	0.842***	0.729***	0.295	0.856***
	(0.193)	(0.184)	(0.184)	(0.195)	(0.215)	(0.211)
Over 65 (%)	3.864***	3.860***	3.868***	3.818***	3.524***	4.177***
	(0.141)	(0.127)	(0.127)	(0.129)	(0.131)	(0.147)
Constant	538.3***	722.4***	725.4***	727.5***	746.3***	727.7***
	(18.271)	(21.323)	(21.333)	(22.582)	(23.331)	(21.897)
F Statistic				6.80***	12.60***	0.386
p-value				0.009	0.000	0.535
N	67,416	67,416	67,416	64,904	57,334	46,631
R2-Overall	0.58	0.49	0.48	0.48	0.45	0.51
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the natural logarithm of the mortality rate per 100,000 population. All specifications include county and time fixed effects. Sample period is 1990-2013 except in last two columns where it starts in 1994 in the first and ends in 2007 in the second. The *p*-value is for the test of the null: $\beta + \pi \neq \delta + \mu$. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Column 4 presents the estimates of (2) without restricting any of the coefficients. All of the coefficients upon the respective *UR* and *POP* components are statistically significant. Moreover, the null hypothesis that $\beta + \pi \neq \delta + \mu$ is easily rejected. To better understand the marginal effects, *Figure 2.1* presents the marginal effect that unemployment has upon mortality across different values for *POP* and for both increases and decreases in the unemployment rate. In the sample, *POP* ranges from 4.01 to 16.12, providing the reason for our use of 4 and 16 as endpoints in the figure. The coefficient upon unemployment for both *UR+* and *UR-* goes from negative to positive for a value of *POP* of around eight which corresponds to a population size of about 3,000. However, the steeper slope for the *UR-* coefficient provides for a lower value of *POP* for which this coefficient is positive and significantly different from zero: *POP* = 10 (corresponding to a population of 22,000) versus *POP* = 12 (163,000). These are vast differences in county sizes. Therefore, the influence of county population as to how unemployment impacts mortality is much stronger for periods of falling unemployment.

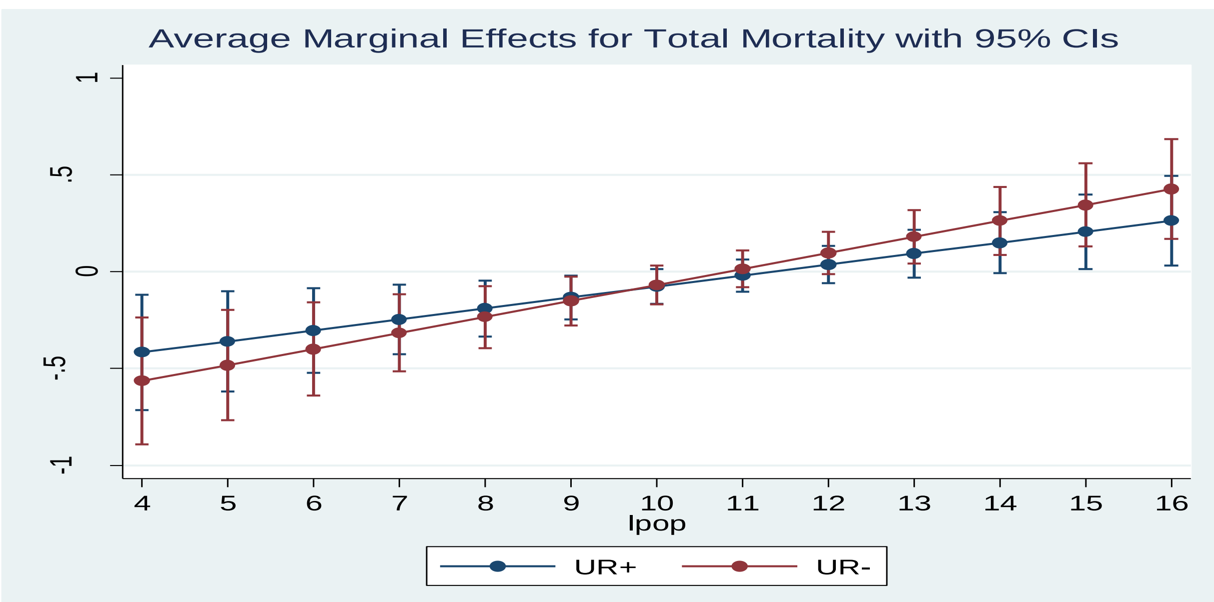

Figure 2.1: Average Marginal Effects for Total Mortality Rate

To summarize the results in column (4), stating that mortality is pro-cyclical or counter-cyclical is overly simplistic. In small counties, mortality is pro-cyclical: increases in unemployment decrease mortality and decreases in unemployment increase it. In large counties, the opposite is true as mortality becomes countercyclical. Mortality increases with rising unemployment. What this also suggests is that the findings from Ruhm (2000) and many subsequent studies are driven by the association between unemployment and mortality within smaller counties. But we also find evidence of an asymmetry. Comparing the marginal effects of unemployment upon mortality, the slope is greater for the *UR*- line. The size of the county is more influential in determining the association between unemployment and mortality during periods of falling unemployment. Before continuing with this discussion, we will examine how modifications to our sample influence results.

Columns 5 and 6 remove two of the three recessions that occurred during the sample window. Column 5 removes the years 1990-1993 whereas column 6 removes the Great Recession and its aftermath, 2008-2013. Results are robust in the first case but not in the latter as what transpired during the Great Recession largely drives results. This is not surprising in that changes in the unemployment rate were greatest during this period and so removal of the Great Recession does the most to lower the variation for unemployment, making it more difficult to find associations. But on the other hand, the importance of the Great Recession in driving findings questions their general applicability.

As for the other control variables, counties with high percentages of whites and high percentages of African-Americans both have higher mortality rates. Moreover, counties with more young children or senior citizens also have higher mortality rates, not surprising given the greater vulnerability of the very young and, especially, the elderly to death.

2.4.2 Demographic Subgroups

Table 2.3 considers subsamples of males versus females and whites versus blacks. To ease the comparison, column 1 presents results of total mortality rate. Columns 2 and 3 consider gender and show that the associations found in column 5 of Table 2.1 pertain more extensively for male mortality than for female mortality. Columns 4 and 5 consider race. Associations remain strong for African-Americans and coincide with what was found above.

Table 2.3: Asymmetry Results by Gender and Ethnicity

	(1)	(2)	(3)	(4)	(5)
	Total	**Male**	**Female**	**White**	**Black**
UR+	-0.643***	-0.882***	-0.352	-0.383	-0.964**
	(0.235)	(0.258)	(0.272)	(0.249)	(0.412)
UR-	-0.896***	-1.099***	-0.666**	-0.694**	-1.281***
	(0.259)	(0.282)	(0.308)	(0.272)	(0.465)
POP*UR+	0.057***	0.084***	0.022	0.037	0.122***
	(0.021)	(0.023)	(0.024)	(0.023)	(0.038)
POP*UR-	0.083***	0.107***	0.053*	0.068***	0.157***
	(0.024)	(0.026)	(0.028)	(0.025)	(0.042)
POP	-16.02***	-16.25***	-15.97***	-14.45***	-47.07***
	(1.231)	(1.282)	(1.413)	(1.429)	(2.835)
White (%)	0.617***	0.429**	0.778***	0.216	-1.307***
	(0.162)	(0.169)	(0.216)	(0.301)	(0.329)
Black (%)	0.979***	0.752***	1.151***	1.367***	-2.371***
	(0.185)	(0.196)	(0.239)	(0.326)	(0.398)
Under 5 (%)	0.729***	1.177***	0.088	0.209	1.585***
	(0.195)	(0.224)	(0.234)	(0.211)	(0.561)
Over 65 (%)	3.818***	4.192***	3.397***	3.838***	2.807***
	(0.129)	(0.145)	(0.137)	(0.136)	(0.278)
Constant	727.5***	746.9***	715.0***	747.3***	1,293.0***
	(22.582)	(23.388)	(28.824)	(38.577)	(48.469)
F Statistic	6.800***	3.115*	6.444**	8.406***	2.753*
p-value ($\beta+\pi = \delta+\mu$)	0.009	0.078	0.011	0.004	0.097
N	64,904	64,624	64,477	64,680	30,113
R2-Overall	0.48	0.47	0.43	0.46	0.27
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the natural logarithm of the mortality rate per 100,000 population. All specifications include county and time fixed effects. The *p*-value is for the test of the null: $\beta + \pi \neq \delta + \mu$. Sample period is 1990-2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4 considers different age groups: infants, young adults (20-44), middle-aged adults (45-65), the elderly (65+), and the seniors (85+). The results do not suggest any evidence of asymmetries for these age groups nor do they indicate any differences between smaller and larger counties.

Table 2.4: Asymmetry Results by Age

	(1)	(2)	(3)	(4)	(5)
	< 1 Year	**20-44 Years**	**45-64 Years**	**≥ 65 Years**	**≥ 85 Years**
UR+	-1.189	-0.051	-0.013	-0.298	0.455
	(1.348)	(0.602)	(0.328)	(0.236)	(0.339)
UR-	0.964	0.080	0.163	-0.258	0.075
	(1.547)	(0.670)	(0.368)	(0.261)	(0.375)
POP*UR+	0.109	-0.028	-0.010	0.030	-0.049*
	(0.106)	(0.055)	(0.029)	(0.021)	(0.030)
POP*UR-	-0.070	-0.036	-0.026	0.029	-0.010
	(0.123)	(0.061)	(0.033)	(0.024)	(0.033)
POP	-21.76***	-32.17***	-16.65***	-15.93***	-4.49***
	(3.786)	(2.644)	(1.563)	(1.142)	(1.499)
White (%)	2.525***	3.731***	1.244***	0.595***	1.161***
	(0.397)	(0.542)	(0.280)	(0.130)	(0.159)
Black (%)	3.553***	4.245***	1.505***	0.819***	0.853***
	(0.493)	(0.616)	(0.303)	(0.152)	(0.192)
Under 5 (%)	-3.113***	5.695***	4.609***	0.923***	0.827***
	(0.809)	(0.519)	(0.304)	(0.200)	(0.263)
Over 65 (%)	1.167***	4.014***	1.120***	-1.592***	-1.060***
	(0.431)	(0.323)	(0.143)	(0.106)	(0.125)
Constant	698.4***	397.6***	671.0***	973.9***	908.1***
	(62.253)	(71.145)	(35.699)	(19.175)	(25.132)
F Statistic	11.80***	0.348	1.253	0.151	5.93**
p-value ($\beta+\pi = \delta+\mu$)	0.001	0.555	0.263	0.697	0.015
N	12,506	43,624	60,618	64,773	63,211
R2-Overall	0.36	0.17	0.13	0.05	0.04
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the natural logarithm of the mortality rate per 100,000 population. All specifications include county and time fixed effects. The *p*-value is for the test of the null: $\beta + \pi \neq \delta + \mu$. Sample period is 1990-2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.4.3 Causes of Mortality

Tables 2.5 and 2.6 consider several different types of mortality although we only consider types where the number of observations exceed 20,000. Examining mortality due to different types of disease are important because looking at differences across these different types can help uncover explanations for the associations found above. As expected, results greatly differ across the type of death.

Table 2.5: Asymmetry Results by Disease Type

	(1)	(2)	(3)	(4)	(5)
	Infective Diseases	**Nutritional Diseases**	**Circulatory System**	**Respiratory System**	**Digestive System**
UR+	-6.831***	1.659**	0.228	1.146***	-2.512***
	(1.257)	(0.672)	(0.309)	(0.422)	(0.555)
UR-	-8.056***	0.342	-0.013	1.037**	-2.644***
	(1.357)	(0.735)	(0.345)	(0.478)	(0.607)
POP*UR+	0.553***	-0.136**	-0.041	-0.085**	0.221***
	(0.110)	(0.059)	(0.028)	(0.038)	(0.049)
POP*UR-	0.657***	-0.012	-0.019	-0.068	0.235***
	(0.119)	(0.064)	(0.031)	(0.043)	(0.054)
POP	-31.1***	-32.2***	-19.4***	-24.0***	-23.0***
	(4.834)	(3.928)	(1.615)	(2.261)	(2.474)
White (%)	4.985***	0.032	-0.232	2.381***	1.020***
	(0.710)	(0.409)	(0.194)	(0.268)	(0.303)
Black (%)	6.223***	0.916*	0.116	2.613***	1.428***
	(0.852)	(0.495)	(0.218)	(0.307)	(0.373)
Under 5 (%)	2.263**	0.247	-0.449*	1.593***	0.894*
	(1.097)	(0.723)	(0.266)	(0.396)	(0.502)
Over 65 (%)	3.899***	3.012***	4.138***	3.749***	3.783***
	(0.576)	(0.356)	(0.170)	(0.216)	(0.272)
Constant	97.849	647.8***	767.8***	401.9***	446.1***
	(103.247)	(66.568)	(28.069)	(38.786)	(46.367)
F Statistic	8.71***	21.35***	3.02*	0.254	0.266
p-value (β+π=δ+μ)	0.003	0.000	0.082	0.614	0.606
N	22,568	36,377	63,896	55,701	34,007
R2-Overall	0.24	0.43	0.46	0.37	0.40

Notes: Dependent variable is the natural logarithm of the mortality rate per 100,000 population. All specifications include county and time fixed effects. The *p*-value is for the test of the null: $\beta + \pi \neq \delta + \mu$. Sample period is 1990-2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results for deaths caused by diseases of the circulatory system (which includes heart attacks) do not show any strong association with the business cycle nor do deaths caused by neoplasms (cancer). Since air pollution can sometimes lead to such problems and because pollution should be increasing along with production (at least in the short run), the lack of a strong association between unemployment and mortality due to diseases of the circulatory system does not support rising pollution levels as causes of the higher mortality we see in booming economies, a cause argued by Heutel and Ruhm (2013).

Table 2.6: Asymmetry Results by Disease Type

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	External Causes	**Vehicle Accidents**	**Mental Disorders**	**Nervous System**	**Neoplasms**
UR+	-4.932***	4.707***	-11.581***	-3.265***	-0.291
	(0.522)	(0.799)	(1.595)	(0.947)	(0.302)
UR-	-5.695***	5.987***	-14.319***	-3.868***	-0.264
	(0.581)	(0.878)	(1.785)	(1.022)	(0.325)
POP*UR+	0.444***	-0.488***	1.007***	0.341***	0.037
	(0.048)	(0.071)	(0.136)	(0.082)	(0.027)
POP*UR-	0.512***	-0.604***	1.241***	0.405***	0.038
	(0.053)	(0.079)	(0.153)	(0.088)	(0.029)
POP	-26.4***	-44.2***	-12.2***	-21.8***	-15.3***
	(2.233)	(2.620)	(6.536)	(4.158)	(1.334)
White (%)	0.973***	2.158***	-1.132	-0.225	0.757***
	(0.245)	(0.332)	(0.857)	(0.564)	(0.205)
Black (%)	1.615***	2.422***	1.167	0.332	0.760***
	(0.317)	(0.395)	(0.974)	(0.632)	(0.225)
Under 5 (%)	1.588***	3.068***	-10.061***	-3.158***	0.389
	(0.447)	(0.568)	(1.432)	(0.840)	(0.243)
Over 65 (%)	1.759***	-0.060	1.064*	2.922***	3.937***
	(0.223)	(0.255)	(0.627)	(0.382)	(0.133)
Constant	569.6***	594.9***	555.8***	542.0***	565.0***
	(36.491)	(47.668)	(123.054)	(74.276)	(27.115)
F Statistic	11.73***	15.23***	29.12***	3.56*	0.043
p-value ($\beta+\pi = \delta+\mu$)	0.001	0.000	0.000	0.059	0.836
N	50,777	25,815	26,171	34,792	62,617
R2-Overall	0.31	0.56	0.38	0.63	0.41

Notes: Dependent variable is the natural logarithm of the mortality rate per 100,000 population. All specifications include county and time fixed effects. The *p*-value is for the test of the null: $\beta + \pi \neq \delta + \mu$. Sample period is 1990-2013. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

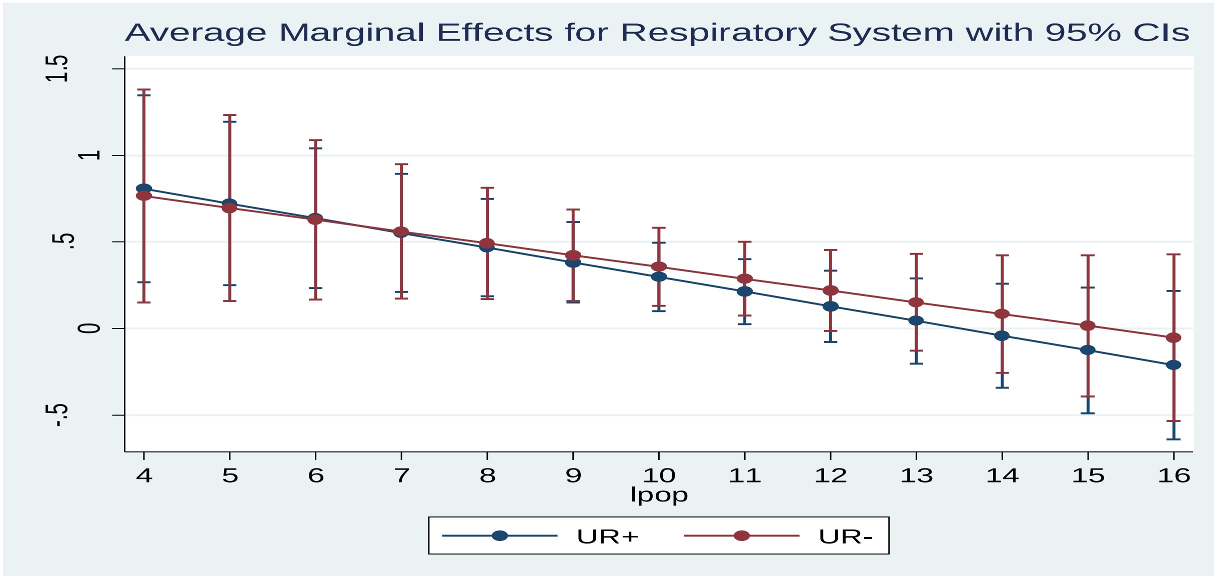

Figure 2.2: Average Marginal Effects for Respiratory System Diseases

Examining diseases due to respiratory problems reinforces this point. *Figure 2.2* presents the marginal effects across population from rising unemployment. Positive associations are found between respiratory mortality and unemployment but only for the smallest counties. Presumably, air pollution is less of a concern in these more rural areas. Moreover, rising unemployment in association with higher mortality rates is counterintuitive if air pollution is leading to more mortality.

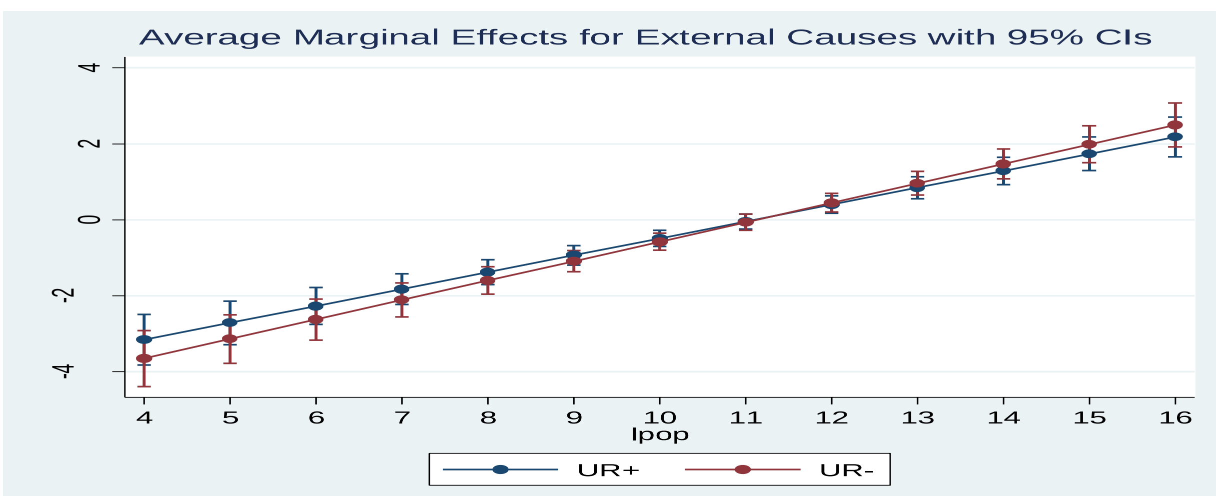

Figure 2.3: Average Marginal Effects for External Causes of Death

Strong results also arise with external causes as the causes of mortality as shown in *Figure 2.3*. Once again, results differ across county size. Deaths due to external causes decrease with unemployment in small counties. One reason for this could be that examples of external causes involve workplace accidents. During weaker economies, not only are fewer people working but a slower pace of economic activity could help workers avoid these accidents. Moreover, many “dangerous” jobs (such as mining, farming, and logging) takes place in rural areas. In large counties, mortality due to external causes is countercyclical, being more prevalent when the economy is weak. Such a finding could arise to the extent that homicides and suicides are more greatly driven by business cycle conditions in cities than they are in rural areas.

2.5 CONCLUSION

This study allows for greater nuance than do many others examining how mortality evolves across the business cycle. For one, we allow for asymmetric associations between the unemployment rate and the mortality rate. Although we often find statistical evidence for an asymmetry, the figures show that the magnitudes do not greatly differ when unemployment is rising versus when it is falling. Nevertheless, a distinction remains and the association between unemployment and mortality is actually stronger in boom times. The question posed in Ruhm (2000): “Are recessions good for your health” perhaps should be reversed to become: “Are booms bad for your health.”

A stronger distinction arises between large and small counties. In small counties, mortality is negatively related with unemployment and so is pro-cyclical. In large counties, however, mortality is countercyclical. A possible explanation is that in smaller counties, seeking medical treatment could involve greater opportunity costs as seeing doctors and, especially, specialists could require long commutes. Recessions could then lower the opportunity costs of visiting doctors and clinics. But mortality is countercyclical in larger counties. Weaker economies tend to lead to higher mortality.

These findings hold over various demographic groups. However, findings weaken when focusing upon age groups regardless of the age group we consider. This is surprising given how strong results are for the total sample. Exploring these distinctions is one avenue of future research.

Results also differ across the types of death. Although most types of death follow the pattern for overall mortality, exceptions do arise such as vehicle accidents and nutritional disease. Others are not significant such as cancer (neoplasms). Of note is that our results refute pollution as an explanation. Presuming that pollution is higher in boom times, then respiratory and circulatory disease should more greatly impact mortality during periods of falling unemployment. Moreover, results should be stronger in larger counties, which again we do not find. Exploring these various causes in greater detail is another avenue of future research.

CHAPTER 3

AN ASYMMETRIC ANALYSIS OF CRIME DURING THE BUSINESS CYLCES

3.1 INTRODUCTION

Crime generates huge social and economic costs (Piquero et al., 2013; McCollister et al., 2010; Detotto and Vannini, 2010; Cohen, 1988), the avoidance of which is crucially important for the sound growth of communities and businesses. That is why many scholars have explored how crime rate varies during cyclical fluctuations proxied by changes in the unemployment rate. However, there is no consensus on the outcome. The literature provides evidence for both positive (Altindag, 2012; Fougere et al., 2009; Lin, 2008; Oster and Agell, 2007; Carmichael and Ward, 2001; Entorf and Spengler, 2000; Britt, 1997) and negative (Andresen, 2015; Phillip and Land, 2012; Kennedy and Forde, 1990; Cantor and Land, 1985) associations between unemployment and crime rates. However, of a review of 63 articles on the link between unemployment and crime, Chiricos (1987) found evidence of a positive association to be three times more prevalent than a negative one.[26]

Exploring this topic is centrally important both to the construction of economic and social theories of crime as well as to the formulation and implementation of social policies. Scholars from various disciplines have attempted to provide theoretical explanations for the unemployment-crime nexus. Some of the most famous theories include strain theory (Merton, 1938), social disorganization theory (Shaw and McKay, 1942), economic or utilitarian theory (Becker, 1968, Ehrlich, 1973, Block and Heineke, 1975), and the opportunity theory of crime (Cantor and Land, 1985).

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[26] Others such as Hagan (1993) and Thornberry and Christenson (1984) exhibit evidence of reciprocal causal relationships between unemployment and criminal involvement.

The strain theory of crime argues that individuals low in the social structure feel frustrated by their failure to gain material attributes of success. When faced with the relative success of others around them, their frustration peaks and finally transforms into crime. Whether crime rise or falls during recessions in this case depends upon whether social gaps widen (or narrow) and so thereby contribute to more (or less) social strain. The social disorganization theory argues that individuals commit crime when the mechanisms of informal social controls become weak or ineffective. Factors that weaken the networks of social control and undermine the ability and willingness of communities to exercise informal control over their members are: poverty, racial heterogeneity, residential mobility, and family instability. To the extent that recessions increases such conditions then crime should increase with the unemployment rate. The economic theory postulates that individuals allocate time between market and criminal activities by comparing the expected returns from each and taking account of the likelihood and severity of punishment. Presumably, the marginal benefit of participating in market activities falls during recessions and so crime should then increase. Last but not the least, the opportunity theory classifies the mechanisms of the unemployment-crime nexus into two segments: a motivation effect and an opportunity effect. The theory assumes that an increase in unemployment has a lagged positive effect on crime through increased motivation, but a contemporaneous negative effect on crime through reduced opportunity as more people stay close to their property. Understanding what theories are most robust provides another reason to empirically study associations between unemployment and crime.

A common assumption in the empirical literature has been that of symmetry.[27] That is, the impact of rising unemployment upon crime is considered to be of the same magnitude as the impact of falling unemployment.[28] Consider the simplified model as an illustration.

$$Crime = \alpha + \beta * Unemployment + \varepsilon \tag{1}$$

A one unit rise in unemployment is predicted to raise crime by β whereas an opposite but equal change in unemployment is predicted to decrease crime by β. However, this assumption of symmetry might not hold and researchers have considered many circumstances where it might not. Hamilton and Lin (1996) and Schwert (1989) find that stock return volatility is higher during recessions in comparison to expansions. Similarly, Kilian and Vigfusson (2011), Hamilton (2011, 2003, and 1983) and Mork (1989) find that oil price shocks have asymmetric impacts on macroeconomic conditions in the United States. Chen (2007) finds that contractionary monetary policy seems to have much larger effects during bear-market periods than the effects during bull-market periods.

Closer to our study, Mocan and Bali (2010) [MB] find that rising unemployment is more strongly associated with rising property crime than falling unemployment is associated with diminishing property crime. However, they do not find evidence of an asymmetry for violent crime. MB use state-level data in their analysis. One difference in our study is that we will use county-level data. Use of county-level data allows for more cross-sectional units although the

[27] Mocan and Bali (2010) consider crime across the business cycle using the U.S. state level crime data and find statistically significant evidence of asymmetry for property crimes but not for violent crimes.

[28] D'Alessio et al. (2014) provide evidence of an inverted U-shaped association between unemployment and the probability of repeat offending, suggesting that unemployment influences criminal activity of repeat and first time offenders in different ways.

time dimension diminishes due to data being available for fewer years. Another advantage is that a smaller unit of analysis can provide a tighter correspondence between the business cycle conditions and crime. Consider California with many municipalities where economic and social conditions could vary within the state. However, a disadvantage of county-level data is that reporting errors could be larger as such errors could be more frequent with less aggregated data as reported in Pierce and Denison (2006). Nevertheless, the MB results provide important insights and we can explore to what extent their findings hold using a different unit of analysis.

A second advantage of using county-level data is that we can examine whether there are particular settings where associations between unemployment and crime are particularly strong. For instance, if the association is stronger in urban than in rural areas, then this could suggest that the explanation for these associations stems from factors more common to urban areas. Deller and Deller (2011) and Lee and Ousey (2001) provide statistical evidence for significant urban-rural crime differences. Moreover, the recent report of the Federal Bureau of Investigation (FBI) indicates that the prevalence of violent crime rate is higher in urban than in rural areas.[29] Glaeser and Sacerdote (1996) also find higher crime rates in cities than in rural areas. However, Myers et al. (2013) report opposite results, suggesting that the injury death rates in urban counties are significantly lower than those in rural counties. Ruback and Menard (2001) find that rates of sexual victimization are higher in rural counties within Pennsylvania as compared to urban counties. Similarly, Peek-Asa et al. (2011) and Pruitt (2008) report higher prevalence of intimate partner violence in rural areas.[30] Therefore, we will also examine to what extent findings could differ between urban and rural areas, thereby requiring a more refined unit of analysis than

[29] Source link: http://victimsofcrime.org/docs/default-source/ncvrw2015/2015ncvrw_stats_urbanrural.pdf?sfvrsn=2

[30] See Sandberg (2013) for a more detailed analysis of urban-rural differences in female victimization.

the state. Many rural areas can be found even in states as populous as California and Texas and so denoting observations from these states as “large” would incorrectly subsume these rural areas into this category. Of course, uniformity need not exist across counties either, but the degree of dissimilarities across counties is likely to be much smaller.

In summary, we will allow associations between crime and unemployment to differ across two dimensions: rising versus falling unemployment and populous versus sparse counties. The remainder of the paper is organized as follows: Section 3.2 describes the data and section 3.3 presents the methodology. Section 3.4 provides results and Section 3.5 concludes.

3.2 DATA

Our sample spans the 24 years from 1990 to 2013 and includes three recessions: 1990-91, 2001, and 2007-09. Data comes mainly from four sources: (a) the Bureau of Labor Statistics (BLS), (b) the Census Bureau, (c) the Uniform Crime Reporting (UCR) System of the FBI, and (d) the Compact Mortality Files (CMF). Data for county unemployment rates is obtained from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS) in the U.S. Department of Labor.[31] Data on unemployment before 1990 is not compatible with subsequent data and the BLS cautions using them together. The unemployment rate we use corresponds to U-3 (the official unemployment rate) and is calculated as the number of unemployed people as a percentage of the labor force. The crime dataset is obtained from two sources. Crime data from 1990 to 2008 is obtained from the U.S. Bureau of the Census and data from 2009 to 2013 is obtained from the Uniform Crime Reporting (UCR) System of the Federal

[31] Data link: http://www.bls.gov/lau/

Bureau of Investigation, U.S. Department of Justice.[32] The crime data is divided into two broad categories: violent crimes and property crime. Violent crimes are further divided into four subcategories: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. Property crimes are further divided into three subcategories: burglary, larceny-theft, and motor vehicle theft. The population demographics data is obtained from the CMF of the Center for Disease Control and Protection. Unless otherwise stated, all crime rates are calculated as the number of crimes per 100,000 people.

Table 3.1: Summary Statistics

Variables	**Obs**	**Mean**	**S.D.**	**Min**	**Max**
Dependent Variables					
Total Violent Crime	69914	389.24	2938.81	0	174626
Murder	69914	4.72	37.64	0	2246
Forcible Rape	69914	23.94	98.84	0	4211
Robbery	69914	128.56	1374.93	0	100332
Aggravated Assault	69914	247.15	1636.73	0	88770
Total Property Crime	69914	2815.39	12893.59	0	536669
Burglary	69914	625.62	2805.66	0	128909
Larceny Theft	69914	1849.13	7711.81	0	269515
Vehicle Theft	69914	341.09	2592.94	0	147134
Independent Variables					
County Unemployment	75287	6.29	2.96	0.40	40.80
County Population	75345	90767.09	294877.20	55	10000000
Percent of Whites	75345	87.75	16.17	2.68	100
Percent of Blacks	67583	10.13	15.08	0.02	86.90
Percent of Under 5	75300	6.47	1.19	1.74	18.46
Percent of Over 65	75329	15.24	4.30	1.18	51.60

Note: Crime values show the number of crimes over a year.

Table 3.1 provides summary statistics of the data. Aggravated assault is the most prevalent type of violent crime and larceny theft comprises the lion's share of property crime. *Figure 3.1* exhibits the relationship between the national unemployment rate and the growth rates

[32] Data link: http://www.ucrdatatool.gov/Search/Crime/State/RunCrimeStatebyState.cfm

of total violent crimes and total property crimes. The two crime growth rates are shown to be positively correlated, but there is a slightly negative association between the unemployment rate and the crime growth rates. Of course, *Figure 3.1* only shows unconditional correlations and does not allow for variation within the United States. Section III allows for such possibilities.

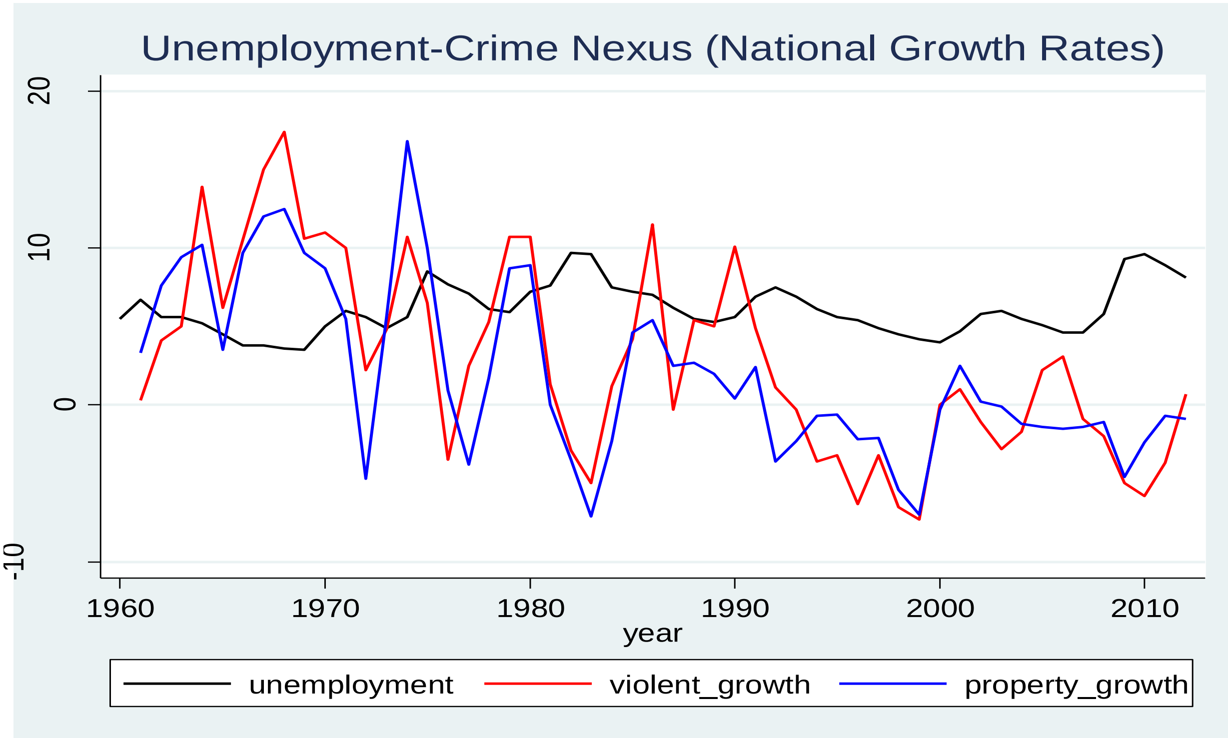

Figure 3.1: Unemployment-Crime Nexus

3.3 METHODOLOGY

In contrast to many crime models, we allow the crime rate to be an asymmetric function of the unemployment rate where the conditional mean of the crime rate is defined to follow two different paths depending on whether the unemployment rate is increasing or decreasing. Our empirical model regresses the crime rate in county i at time t (C_{it}) upon UR_{it}^{+} and UR_{it}^{-}, which are formally defined below. We also include several county-year control variables contained in

X_{it} along with time-invariant county fixed effects (α_i), county-invariant time fixed effects (θ_t) and the regression error term (ε_{it}):

$$C_{it} = \alpha_i + \theta_t + \beta UR_{it}^{+} + \delta UR_{it}^{-} + \pi POP_{it} UR_{it}^{+} + \mu POP_{it} UR_{it}^{-} + \gamma X_{it} + \varepsilon_{it} \qquad (2)$$

The inclusion of fixed effects captures time-invariant unobserved characteristics of counties such as location and geography whereas time fixed effects control for variations across years that are consistent across counties such as changes in federal government policies. Matrix X_{it} includes the percentage of whites in the county, the percentage of African-Americans, the percentage of people under five years of age, and the percentage of people aged 65 and above. The natural log of the county population is also included in X_{it} as well as in the interactive terms. Following Mocan and Bali (2010), we define the variables UR_{it}^{+} and UR_{it}^{-} as:

$$UR_{it}^{+} = UR_{it} \;\; if \;\; UR_{it} \geq UR_{it-1} \;\; and \;\; = \;\; 0, \;\; otherwise \qquad (3)$$

$$UR_{it}^{-} = UR_{it} \;\; if \;\; UR_{it} < UR_{it-1} \;\; and \;\; = \;\; 0, \;\; otherwise \qquad (4)$$

UR_{it}^{+} is nonzero only in cases where the unemployment rate is equal to or higher than what it was in the previous period. UR_{it}^{-}, on the other hand, is nonzero only when the unemployment rate is lower than it was the previous year. If different effects arise then $\beta + \pi \neq \delta + \mu$. This asymmetry exists even if $\pi = \mu = 0$ although county size in this case would not impact the influence that unemployment has upon mortality.

3.4 RESULTS

Table 3.2 presents the estimates of equation (2) but first restricts some of the coefficients to be zero so as to begin with a more parsimonious model. The results in Table 3.2 do not allow for any asymmetry. The main coefficient of interest, county unemployment rate, is found to be negative in the case of violent crimes but positive, albeit insignificant, in the case of property crimes. These signs suggest that violent crime decreases during recessions whereas no evidence arises that property crime is associated with the business cycle. Adding the natural log of population as a control variable in columns 3 and 4 produces similar results although the coefficient upon property crime is now significant at the 10% level, suggesting that violent and property crime respond oppositely over the business cycle. The negative coefficient upon *POP* in column 4 suggests that the rate of property crime is lower in larger counties.

Table 3.2: Fixed Effects Estimates: Baseline Total Crime Rate Regressions

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Violent	**Property**	**Violent**	**Property**	**Violent**	**Property**
County UR	-4.475***	5.595	-4.462***	10.194*	62.168***	584.284***
	(1.010)	(5.878)	(1.010)	(5.748)	(10.510)	(45.390)
POP			-2.242	-797.77***	50.480**	-333.510**
			(24.447)	(163.160)	(24.017)	(166.435)
POP*UR					-6.389***	-55.088***
					(1.027)	(4.437)
White (%)	27.347***	294.576***	27.298***	275.902***	24.828***	254.272***
	(4.945)	(26.613)	(5.045)	(26.900)	(5.171)	(26.532)
Black (%)	25.015***	222.660***	24.966***	204.001***	23.660***	192.786***
	(5.907)	(31.168)	(5.989)	(31.999)	(6.033)	(31.421)
Under 5 (%)	28.608***	124.520***	28.614***	126.200***	27.539***	115.202***
	(4.842)	(24.773)	(4.835)	(24.555)	(4.893)	(24.423)
Over 65 (%)	14.972***	61.629***	14.968***	60.742***	14.253***	54.879***
	(2.280)	(13.501)	(2.286)	(13.310)	(2.270)	(13.106)
Constant	-2,730***	-27,107***	-2,702***	-17,041***	-3,004***	-19,696***
	(504.908)	(2,650.626)	(626.924)	(3,370.481)	(605.302)	(3,337.319)
N	55,882	57,718	55,882	57,718	55,882	57,718
R2-Within	0.23	0.44	0.23	0.44	0.24	0.45

Notes: Crime rate is defined as (number of crimes/population)*100,000. All specifications include county and time fixed effects. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The last specifications in columns 5 and 6 allow the coefficient upon *UR* to differ with the natural log of the population. The signs for both property crime and violent crime are similar and suggest that both general types of crime are pro-cyclical in counties where *POP* is less than ten but countercyclical in larger counties. A value for *POP* of ten corresponds to a county of around 22,000 people.

Table 3.3: Asymmetric Violent Crime Rate Regressions

	Violent Crime	**Murder**	**Rape**	**Robbery**	**Assault**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
UR+	60.405***	0.505**	5.397***	15.376**	35.610***
	(10.624)	(0.249)	(0.635)	(7.321)	(5.888)
UR-	73.966***	0.612**	6.926***	20.949***	42.512***
	(11.462)	(0.260)	(0.758)	(7.598)	(6.581)
POP* UR+	-6.193***	-0.051**	-0.501***	-1.528**	-3.700***
	(1.038)	(0.023)	(0.058)	(0.709)	(0.557)
POP* UR-	-7.472***	-0.061**	-0.644***	-2.062***	-4.321***
	(1.117)	(0.024)	(0.069)	(0.734)	(0.622)
POP	64.120**	-0.409	-1.323	40.941***	36.821*
	(25.495)	(0.567)	(2.352)	(7.741)	(20.080)
White (%)	25.217***	0.067	0.695	12.077***	14.669***
	(5.037)	(0.089)	(0.526)	(3.142)	(2.754)
Black (%)	25.327***	0.161	0.339	11.505***	15.975***
	(5.903)	(0.112)	(0.570)	(3.538)	(3.296)
Under 5 (%)	30.777***	0.562***	1.202**	10.883***	20.585***
	(5.017)	(0.149)	(0.567)	(2.181)	(3.780)
Over 65 (%)	16.054***	0.431***	1.009***	6.686***	10.322***
	(2.355)	(0.067)	(0.214)	(0.924)	(1.872)
Constant	-3,224***	-4***	-43***	-1,711***	-1,857***
	(592.244)	(11.779)	(62.309)	(352.763)	(366.269)
F Statistic ($\beta+\pi = \delta+\mu$)	45.145***	1.360	25.586***	44.703***	17.908***
p-value ($\beta+\pi = \delta+\mu$)	0.000	0.244	0.000	0.000	0.000
N	53,627	28,444	44,713	41,485	53,714
R2-Within	0.25	0.08	0.12	0.20	0.20
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Notes: Crime rate is defined as (number of crimes/population)*100,000. All specifications include county and time fixed effects. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

As for the other control variables, counties with high percentages of whites and high percentages of African-Americans both have higher crime rates. Moreover, counties with more young children or senior citizens also have higher crime rates. Although the very young and very old are generally not perpetrators of crime, they can make for easy victims. Moreover, counties with high fractions of young could also be poorer counties. According to social disorganization theory, poverty is one of the factors that weaken the networks of social control which ultimately could lead to increase in crime.

Table 3.4: Asymmetric Property Crime Rate Regressions

	Property Crime	**Burglary**	**Larceny Theft**	**Vehicle Theft**
	(6)	**(7)**	**(8)**	**(9)**
UR+	570.470***	95.629***	408.003***	62.789***
	(45.033)	(11.178)	(28.364)	(10.977)
UR-	689.861***	119.392***	491.767***	74.835***
	(50.638)	(12.551)	(32.434)	(11.539)
POP* UR+	-53.634***	-8.494***	-38.424***	-6.218***
	(4.390)	(1.091)	(2.727)	(1.085)
POP* UR-	-64.902***	-10.673***	-46.369***	-7.350***
	(4.938)	(1.225)	(3.125)	(1.138)
POP	-254.345	-116.795***	-192.157	47.985**
	(167.778)	(40.400)	(123.604)	(18.731)
White (%)	250.103***	51.731***	166.179***	33.073***
	(26.951)	(6.462)	(17.859)	(4.911)
Black (%)	191.766***	46.597***	118.984***	27.142***
	(31.901)	(7.977)	(21.083)	(5.613)
Under 5 (%)	109.301***	44.822***	43.055**	24.330***
	(25.156)	(6.699)	(17.863)	(4.178)
Over 65 (%)	62.005***	21.831***	33.439***	8.797***
	(13.505)	(3.377)	(10.012)	(1.523)
Constant	-20,159***	-3,683***	-12,762***	-3,770***
	(3,344.723)	(774.680)	(2,362.299)	(549.624)
F Statistic ($\beta+\pi = \delta+\mu$)	126.360***	72.080***	126.009***	45.742***
p-value ($\beta+\pi = \delta+\mu$)	0.000	0.000	0.000	0.000
N	55,352	55,007	55,155	53,386
R2-Within	0.46	0.33	0.46	0.26
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Notes: Crime rate is defined as (number of crimes/population)*100,000. All specifications include county and time fixed effects. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Tables 3.3 and 3.4 present the estimates of (2) without restricting any of the coefficients for violent and property crimes, respectively and so allowing for an asymmetry to arise. All of the coefficients upon the respective *UR* and *POP*UR* components are statistically significant. Moreover, the null hypothesis of symmetry that $\beta + \pi = \delta + \mu$ is easily rejected for all types of crime except murder. To better understand the marginal effects from the results of (2), *Figures 3.2* and *3.3* present the marginal effect that unemployment has upon violent and property crime, respectively, across different values for *POP* and for both increases and decreases in the unemployment rate. In the sample, *POP* ranges from 4.01 to 16.12, providing the reason for our use of 4 and 16 as endpoints in the figures. The coefficients upon unemployment for both UR^{+} and UR^{-} go from positive to negative for a value of *POP* of around ten for violent crime and eleven for property crime which corresponds to a population size of about 22,000 for violent crime and 60,000 for property crime. However, the steeper slope for the UR^{-} coefficient provides for a lower value of *POP* for which this coefficient is positive and significantly different from zero. Therefore, the influence of county population as to how unemployment impacts crime is much stronger for periods of falling unemployment.

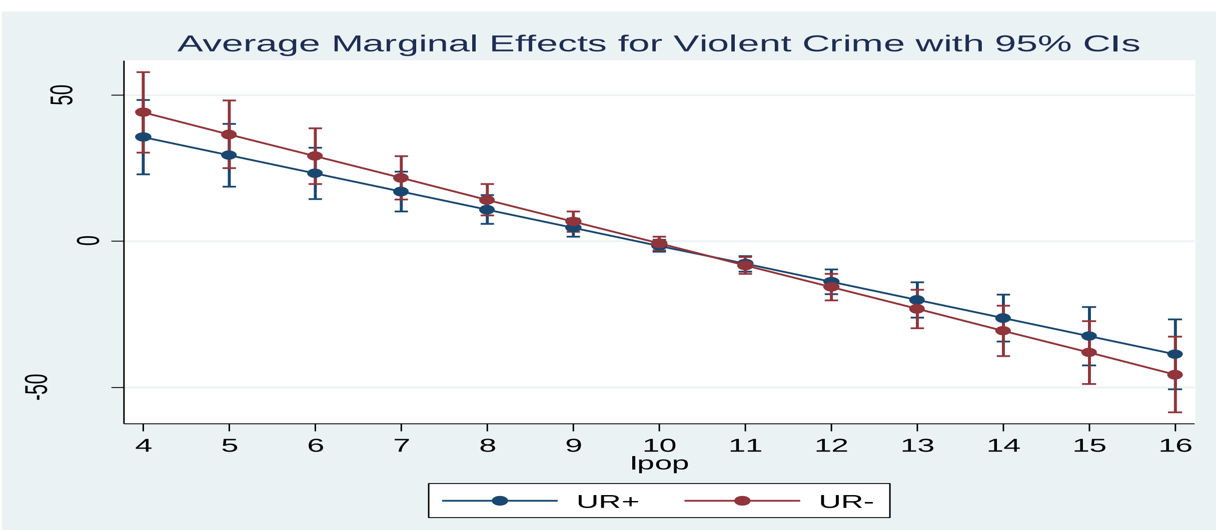

Figure 3.2: Average Marginal Effects for Violent Crime Rate

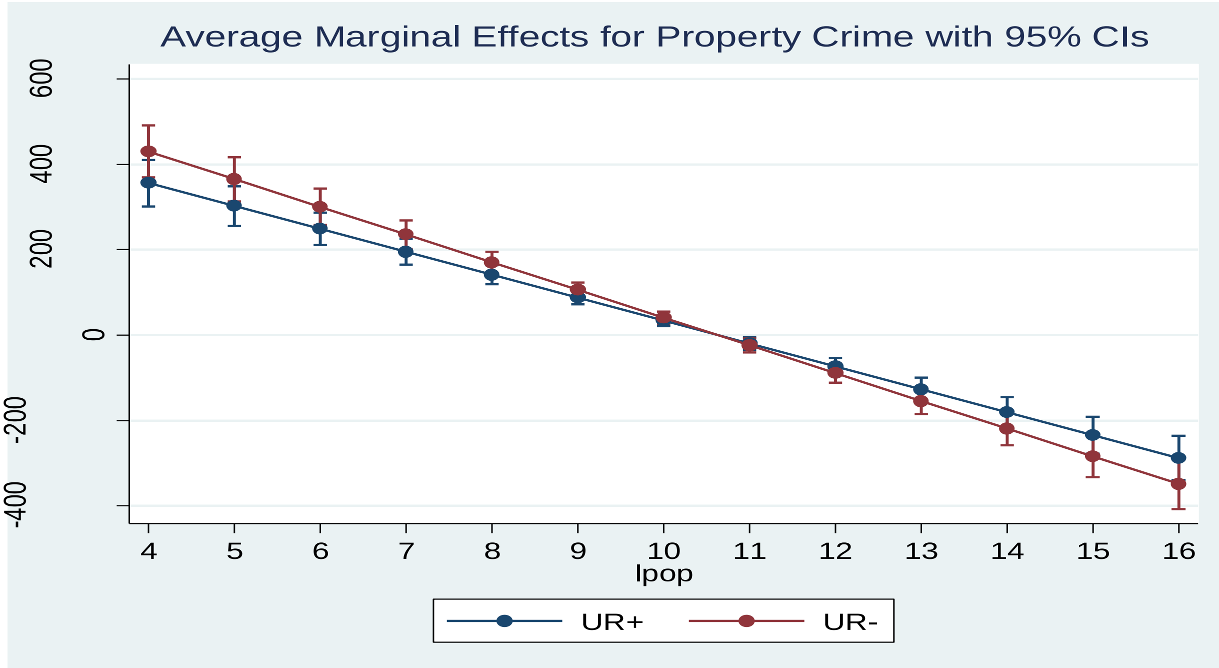

Figure 3.3: Average Marginal Effects for Property Crime Rate

In summary, stating that crime is pro-cyclical or countercyclical is overly simplistic. In large counties, crime is pro-cyclical: increases in unemployment decrease crime and decreases in unemployment increase it. In small counties, the opposite is true as crime becomes countercyclical. Crime increases with rising unemployment. But we also find evidence of an asymmetry. Comparing the marginal effects of unemployment upon crime, the slope is greater for the UR^{-} line. The size of the county is more influential in determining the association between unemployment and crime during periods of falling unemployment.

3.5 CONCLUSION

Using the U.S. county level data on different categories of violent and property crime over a period of 24 years from 1990 to 2013, we explore the association between the business cycles and crime rates. Both violent and property crime are countercyclical in small counties but pro-cyclical in large ones. Such results can have important policy implications. Local government budgets are often tightened in economic downturns, including funds for policing. The relative impact of such tightening could be more strongly felt in smaller counties where increases in crime would accompany such expenditures. Larger counties could be less affected.

Moreover, the results suggest that theoretical approaches on crime and the business cycle should also be more nuanced as all-encompassing theories could be too coarse. Some characteristics of cities either reduce the negative effects of downturns or cause people to behave differently across the business cycle, at least in regards to criminal activity. Exploring potential characteristics will be a focus of later work.

Finally, evidence arises for asymmetric effects for all types of crime other than murder. Falling unemployment appears to have a larger impact upon the prevalence of crime than does rising unemployment as the slopes in *Figures 3.2* and *3.3* are steeper for UR^{-}. Nevertheless, the magnitudes of these differences do not appear to be large.

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APPENDICES

APPENDIX A

This appendix lists type of death under each coding system and then shows that results are robust to the type of coding system considered. Each system is listed in Tables A1 and A2.

Table A1: List of ICD-9 Diagnosis Codes

ICD-9 Code	Description
001-139	Infectious and Parasitic Diseases
140-239	Neoplasms
240-279	Endocrine, Nutritional and Metabolic Diseases, and Immunity Disorders
280-289	Diseases of the Blood and Blood-Forming Organs
290-319	Mental Disorders
320-389	Diseases of the Nervous System and Sense Organs
390-459	Diseases of the Circulatory System
460-519	Diseases of the Respiratory System
520-579	Diseases of the Digestive System
580-629	Diseases of the Genitourinary System
630-679	Complications of Pregnancy, Childbirth, and the Puerperium
680-709	Diseases of the Skin and Subcutaneous Tissue
710-739	Diseases of the Musculoskeletal System and Connective Tissue
740-759	Congenital Anomalies
760-779	Certain Conditions Originating In the Perinatal Period
780-799	Symptoms, Signs, and Ill-Defined Conditions
E800-E999	External Causes of Injury and Poisoning

The sample period spans two revisions of the International Classification of Diseases (ICD) codes for the underlying causes of death - ICD-9 and ICD-10, produced by the World Health Organization (WHO). ICD-9 codes are used during 1979-1998 whereas ICD-10 codes are used during 1999-present.[33,34] In order to provide a reasonable comparison among these codes, NCHS employed comparability ratios based on the relative number of cause-specific deaths in 1976 for reconciling ICD-8 and ICD-9 classifications (Ruhm, 2013; Klebba and Scott, 1980) and in 1996 for reconciling ICD-9 and ICD-10 classifications (Anderson et al., 2001). Though the

[33] For details, go to: http://www.icd9data.com/2015/Volume1/

[34] For details, visit: http://www.icd10data.com/ICD10CM/Codes

comparison is not perfect, an effort has been made to reconcile these codes for cause-specific mortality rates to provide a comparable estimation.

Table A2: List of ICD-10 Diagnosis Codes

ICD-10 Code	Description
A00-B99	Certain Infectious and Parasitic Diseases
C00-D49	Neoplasms
D50-D89	Diseases of the Blood and Blood-Forming Organs and Certain Disorders Involving the Immune Mechanism
E00-E89	Endocrine, Nutritional and Metabolic Diseases
F01-F99	Mental, Behavioral and Neurodevelopmental Disorders
G00-G99	Diseases of the Nervous System
H00-H59	Diseases of the Eye and Adnexa
H60-H95	Diseases of the Ear and Mastoid Process
I00-I99	Diseases of the Circulatory System
J00-J99	Diseases of the Respiratory System
K00-K95	Diseases of the Digestive System
L00-L99	Diseases of the Skin and Subcutaneous Tissue
M00-M99	Diseases of the Musculoskeletal System and Connective Tissue
N00-N99	Diseases of the Genitourinary System
O00-O99	Pregnancy, Childbirth and the Puerperium
P00-P96	Certain Conditions Originating in the Perinatal Period
Q00-Q99	Congenital Malformations, Deformations and Chromosomal Abnormalities
R00-R99	Symptoms, Signs and Abnormal Clinical and Laboratory Findings, Not Elsewhere Classified
U00-U99	Codes for Special Purposes
V01-Y89	External Causes of Morbidity and Mortality

We check robustness of the estimates by using a subsample of our data that spans the period of ICD-10 codes only thereby taking care of any inconsistencies that may exist between the reconciliation of the two codes. Results are in Table A3 which are very similar to the previous findings of the total sample and shows no strong evidence of inconsistency between the reconciliation of ICD codes.

Table A3: Fixed Effect Estimates Using ICD-10

	All	Urban	Rural	All	Urban	Rural
	All Mortality Rate			**20-44 Year Old Mortality Rate**		
County UR	-0.0017***	-0.0026***	-0.0008	-0.0067***	-0.0080***	-0.0043**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
N	44,463	16,625	27,838	28,540	14,200	14,340
	Male Mortality Rate			**Female Mortality Rate**		
County UR	-0.0012**	-0.0023**	-0.0004	-0.0026***	-0.0031***	-0.0015*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	44,213	16,608	27,605	44,108	16,596	27,512
	White Mortality Rate			**Black Mortality Rate**		
County UR	-0.0008	-0.0019*	0.0004	-0.0005	-0.0011	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
N	44,291	16,623	27,668	19,780	11,163	8,617
	45-64 Year Old Mortality Rate			**≥ 65 Year Old Mortality Rate**		
County UR	-0.0023***	-0.0022*	-0.0012	-0.0013**	-0.0020**	-0.0006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	41,008	16,374	24,634	44,362	16,615	27,747

Notes: Dependent variable is the natural logarithm of various demographic mortality rate per 100,000 population. All specifications also include county and time fixed effects as well as controls for the percentage of county populations who are white and black and in two age categories (<5 and ≥65 years old). Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

APPENDIX B

The results from the text allow all coefficients to vary between urban and rural counties. A more restrictive model is shown in (2) and only allows coefficients on the unemployment rate to vary between urban and rural counties. Tables B1 and B2 present results when we estimate (2). Table B1 presents results when D = 1 for all counties having more than 50,000 people whereas Table B2 presents results when D = 1 for all counties having more than 100,000 people.

Results from Table B1 coincide with what is reported in the text. Mortality is more pro-cyclical in urban counties but more so for females. Death due to diseases of the heart and circulatory systems are more pro-cyclical in urban areas whereas external accidents are more pro-cyclical in rural counties. Some differences, however, also arise. Stronger evidence now arises that mortality due to pneumonia and influenza is more pro-cyclical in urban areas which could be explained by our pollution story. Moreover, mortality for all adults is now more pro-cyclical in urban areas. In Table B2, stronger associations are found between unemployment and mortality in counties with more than 100,000 people.

Table B1: Results of Interactive Model with 50,000 Threshold

Mortality Rate	County UR	Urban*UR
All Mortality Rate	-0.0012**	-0.0008
	(0.000)	(0.001)
Male Mortality Rate	-0.0010**	-0.0003
	(0.001)	(0.001)
Female Mortality Rate	-0.0017***	-0.0010
	(0.001)	(0.001)
White Mortality Rate	-0.0006	-0.0007
	(0.000)	(0.001)
Black Mortality Rate	0.0025**	-0.0030**
	(0.001)	(0.001)
20-44 Year Old Mortality Rate	-0.0040***	-0.0041***
	(0.001)	(0.001)
45-64 Year Old Mortality Rate	-0.0019***	-0.0014**
	(0.001)	(0.001)
≥ 65 Year Old Mortality Rate	-0.0002	-0.0013***
	(0.000)	(0.000)
Heart / Circulatory Diseases	-0.0024***	-0.0025***
	(0.001)	(0.001)
Neoplasms / Cancer	0.0004	-0.0010
	(0.001)	(0.001)
Influenza and Pneumonia	-0.0050**	-0.0077***
	(0.002)	(0.002)
External Causes of Death	-0.0040***	0.0026**
	(0.001)	(0.001)
Vehicle Accidents	-0.0056***	-0.0101***
	(0.002)	(0.001)
Liver and Cirrhosis	0.0011	-0.0013
	(0.003)	(0.003)
Respiratory System Diseases	0.0017*	-0.0014
	(0.001)	(0.001)
Nervous System Diseases	0.0047**	0.0016
	(0.002)	(0.002)
Suicides	0.0121***	-0.0076**
	(0.003)	(0.003)
Digestive System Diseases	-0.0014	-0.0003
	(0.001)	(0.001)
Nutritional & Metabolic Diseases	0.0033**	-0.0062***
	(0.002)	(0.002)
Genitourinary System Diseases	0.0006	-0.0060***
	(0.002)	(0.002)

Notes: Dependent variable is natural log of various types of mortality rate per 100,000 people. All specifications include county and time FEs & controls for % of county populations who are white & black & in two age groups. Robust SE in parentheses***p<0.01,**p<0.05,*p<0.1.

Table B2: Results of Interactive Model with 100,000 Threshold

Mortality Rate	**County UR**	**Urban*UR**
All Mortality Rate	-0.0012***	-0.0009*
	(0.000)	(0.000)
Male Mortality Rate	-0.0011**	0.00002
	(0.000)	(0.001)
Female Mortality Rate	-0.0017***	-0.0018***
	(0.001)	(0.001)
White Mortality Rate	-0.0007	-0.0009*
	(0.000)	(0.001)
Black Mortality Rate	0.0030**	-0.0067***
	(0.001)	(0.001)
20-44 Year Old Mortality Rate	-0.0048***	-0.0030**
	(0.001)	(0.001)
45-64 Year Old Mortality Rate	-0.0018***	-0.0032***
	(0.001)	(0.001)
≥ 65 Year Old Mortality Rate	-0.0003	-0.0018***
	(0.000)	(0.000)
Heart / Circulatory Diseases	-0.0026***	-0.0032***
	(0.001)	(0.001)
Neoplasms / Cancer	0.0004	-0.0019***
	(0.001)	(0.001)
Influenza and Pneumonia	-0.0035*	-0.0157***
	(0.002)	(0.002)
External Causes of Death	-0.0042***	0.0055***
	(0.001)	(0.001)
Vehicle Accidents	-0.0062***	-0.0139***
	(0.002)	(0.001)
Liver and Cirrhosis	-0.0025	0.0032*
	(0.002)	(0.002)
Respiratory System Diseases	0.0021**	-0.0040***
	(0.001)	(0.001)
Nervous System Diseases	0.0043**	0.0035**
	(0.002)	(0.002)
Suicides	0.0025	0.0036**
	(0.002)	(0.002)
Digestive System Diseases	-0.0024**	0.0025**
	(0.001)	(0.001)
Nutritional & Metabolic Diseases	0.0016	-0.0042**
	(0.002)	(0.002)
Genitourinary System Diseases	-0.0021	-0.0034*
	(0.002)	(0.002)

Notes: Dependent variable is natural log of various types of mortality rate per 100,000 people. All specifications include county and time FEs & controls for % of county populations who are white & black & in two age groups. Robust SE in parentheses***p<0.01,**p<0.05,*p<0.1.

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